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PRELIMINARY VERSION

Abstract

In this paper, we study the relative importance of demand and technology shocks in generating business cycle fluctuations, both at the aggregate level and at the level of individual industries. We construct a New Keynesian DSGE model that is highly disaggregated at the industry level with an input-output network structure. Measured productivity in the model fluctuates in response to both technology and demand shocks due to endogenous factor utilization. We estimate the model by the simulated method of moments using U.S. industry data from 1960 to 2005.

We find that the aggregate technology shock has zero variance. Exogenous shocks to technology are necessary for our model to fit the data, but these shocks are exclusively industry-specific, uncorrelated across industries. The bulk of the aggregate fluctuations, including those in aggregate measured productivity, are explained through shocks to aggregate demand. This shock structure is supported by a host of information from the disaggregate data.

Our second finding is that about half of the decrease in the cyclicality of measured productivity in the U.S. after the mid-1980s can be explained by the reduction in the size of demand shocks, in line with the narrative of the *great moderation*.

Keywords: business cycles, productivity, industries, factor utilization, input-output linkages, networks.

JEL Classification Numbers: E32, E24, E37.

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1 Introduction

What type of shocks are driving business cycles? Contemporary workhorse DSGE models often feature a wide variety of shocks, the importance of which might vary over time. For many of the commonly used types of these shocks, there are prevailing controversies about whether they can be interpreted as structural sources of the fluctuations, see for example Chari et al. (2009). In contrast, many models in the theoretical literature are still built on the assumption that business cycles are driven solely by technology shocks.

However, the plausibility of aggregate technology shocks, i.e., changes in factor productivity affecting the whole economy, has long been disputed in the macroeconomic literature, see e.g. Summers (1986). These shocks are not directly observed, and are hard to identify. Identification of technology shocks with the use of Solow residuals, for example, suffers from issues regarding the measurement of inputs and outputs, such as composition effects and variable capacity utilization.[1]

Technological changes at the level of narrowly defined industries appear more plausible and probably easier to identify because their fluctuations are larger and therefore less likely to be dominated by mismeasurement. Thus, a branch of literature has emerged that studies whether independent shocks at various levels of disaggregation can explain the aggregate fluctuations. Focusing mostly on the mechanisms that propagate idiosyncratic shocks across the economy within the RBC framework, the conclusion so far is that only a part of the fluctuations in aggregate productivity can be accounted to the independent industry-level shocks, see our summary in section 1.1 for more detail.

In this paper, we study the role of the different types of shocks in generating business cycle fluctuations in a New Keynesian DSGE model, building on the growing literature on multi-industry business cycle models. We calibrate the model to industry-level U.S. data. Our model has the following key characteristics. First, the production of goods is highly disaggregated, composed of 77 industries connected through the input-output network. Second, the economy is driven by technology and demand-side shocks at both the aggregate and the industry level. Third, endogenous factor utilization allows non-technology shocks to generate changes in measured productivity. Fourth, there are nominal rigidities at the firm level, in line with the New Keynesian literature. The nominal rigidities are important because the price mechanism is central for the propagation of shocks via the input-output network. For example, an increase in industry productivity only leads to higher industry output if the prices reflect the change in productivity. While the model features a detailed industry structure, it only includes four types of shocks, less than a typical medium-sized DSGE model. At the aggregate level, our model features one demand side shock and one productivity shock. Additionally, each industry is affected by its own idiosyncratic shock to demand and productivity. We show that this parsimonious shock structure delivers a very good fit of the model along many dimensions at the aggregate and industry level.

We find that although the exogenous shocks to technology are necessary for our model to fit the data, these shocks are exclusively industry-specific. The variance of the aggregate

[1] Further, identification approaches based on structural VAR models rely heavily on the identifying assumptions, see e.g. Erceg et al. (2005).

technology shock is zero. The remaining three types of shocks generate the observed fluctuations of aggregate and industry variables, as well as the co-movement pattern across industry-level variables. The majority of the aggregate fluctuations, including those in aggregate measured productivity, are explained through the shocks to aggregate demand. On the other hand, industry-specific technology and demand shocks are the dominant drivers of fluctuations at the industry level. Industry-specific shocks to technology are necessary to explain the strong fluctuations of measured productivity at the industry level. Moreover, they also contribute a significant part to the volatility of measured productivity at the aggregate level.

Our model can generate the observed fluctuations in aggregate productivity without aggregate technology shocks as a result of the combination of two elements. First, the contribution of industry-level shocks to aggregate productivity, and second, endogenous fluctuations arising from variable factor utilization (effort) and increasing returns to scale (fixed costs). These mechanisms allow non-technology shocks to contribute to fluctuations in measured productivity.

Our results are compatible with recent evidence that the bulk of aggregate macroeconomic fluctuations is driven by one type of shock that has the characteristics of a demand shock, see Angeletos et al. (2020), Andrle et al. (2017). We support these findings by using industry-level evidence, which brings in a host of information that is useful for the identification of shocks. We find that, considering aggregate data only, it is difficult to distinguish a model with aggregate technology shocks from a model that relies on endogenous productivity fluctuations. However, we show that these models have quite different implications for the industry-level variables. One important piece of industry-level evidence is the co-movement of the variables, especially measured productivity, across industries. Moreover, the models differ in their implications for the size of fluctuations of industry variables relative to aggregate variables and for the cyclicality of productivity.

Our second finding is that about a half of the decrease in the cyclicality of measured productivity in the U.S. in the period after 1984 can be explained by the reduction in the size of demand shocks, in line with the narrative of the *great moderation*. We refer to the empirical observations that the procyclicality of measured productivity in the U.S. has to a large extent disappeared in the period after 1984, see Stiroh (2009) and Galí and Gambetti (2009). Several authors, for example Galí and Gambetti (2009) and Barnichon (2010), have suggested that the great moderation period after 1984 was characterised by a different composition of shocks, especially stressing the lower volatility of shocks to aggregate demand, or muted effects of these shocks on the economy. Thus, we assume a lower volatility of the shocks to aggregate demand for the period after 1984, keeping the rest of parameters the same. The correlation between aggregate measured TFP and hours decreases from 0.49 to 0.11, corresponding to 50% of the change observed in the data. Importantly, our model is able to generate the decrease in the procyclicality of the aggregate measured productivity without generating counterfactual changes at the industry level.

The rest of the paper is structured as follows. After discussing the existing literature in section 1.1, we introduce the multi-industry New Keynesian general equilibrium model in section 2. We describe the data sources and the calibration strategy in section 3. Section 4 presents and discusses the results. Finally, section 5 concludes.

1.1 Relationship to the existing literature

Productivity shocks have played a prominent role in macroeconomics over the last four decades. They were the only shocks driving the economic fluctuations in the early RBC models, starting with Kydland and Prescott (1982) and Long and Plosser (1983). In the contemporary medium-sized DSGE models, as they are routinely used in central banks, technology shocks are as a rule included in the set of structural shocks that drive the business cycles. At the same time, these shocks continue to play an important role in the academic literature, e.g. macroeconomic models with financial frictions starting from Kiyotaki and Moore (1997); the literature investigating whether the fluctuations in the unemployment can be explained by the aggregate shocks to productivity (Shimer 2005, Costain and Reiter 2008, Hagedorn and Manovskii 2008, Hall and Milgrom 2008). At the same time, these shocks have been subject to ongoing critique, see for example Francis and Ramey (2005), Chari et al. (2009).

The idea that industry-specific technology shocks might add up to sizeable technology shocks in the aggregate goes back at least to Long and Plosser (1983) and has attracted renewed attention in recent years. The law of large numbers suggests that idiosyncratic shocks at firm or industry level quickly wash out and cannot drive the aggregate fluctuations. However, Horvath (1998), Horvath (2000), Dupor (1999), Acemoglu et al. (2012), and Acemoglu et al. (2017) point out that idiosyncratic shocks might propagate between industries due to input-output linkages and thus affect the aggregate fluctuations more strongly than the law of large numbers would predict. The focus of the papers lies on the properties of the input-output network that amplify the transmission of shocks across industries. They show that network asymmetry with respect to the number of downstream industries is crucial for the ability of the models to generate substantial aggregate fluctuations from industry-specific shocks. Other channels of amplification of the macroeconomic impact of microeconomic shocks are studied in Baqaee (2018) and Baqaee and Farhi (2019). Gabaix (2011) and Carvalho and Gabaix (2013) stress the importance of large firms and the fat-tailed distribution of firm size in generating the aggregate fluctuations.

Following the idea of industry-level shocks propagated through the input-output network, Foerster et al. (2011), Holly and Petrella (2012), Atalay (2017) and vom Lehn and Winberry (2020) use various approaches to quantify the relative importance of both industry-specific and aggregate shocks for the macroeconomic fluctuations. Foerster et al. (2011) use factor analysis to decompose the industrial production series into the aggregate and idiosyncratic components and adjust the results for the contribution of the input-output network. They estimate that industry-specific shocks are responsible for 20% to 50% of the aggregate fluctuations, depending on the sample period (industry specific shocks are more important in the period after the mid-1980s). However, their RBC model only features technology shocks. Holly and Petrella (2012) utilize an industry-level VAR model of the U.S. manufacturing and identify the industry-specific shocks to productivity using the long-run restrictions proposed by Galí (1999) at the industry level. Their estimates are broadly in line with the results of our paper for both aggregate and industry-level fluctuations. They find a very limited role of aggregate shocks to technology, while industry-level shocks to technology play an important role. The industry-specific shocks in Holly and Petrella in general explain a somewhat bigger part of the fluctuations of aggregate variables than in our paper, which can be attributed to a different concept of the industry-specific shock to demand.

Atalay (2017) and vom Lehn and Winberry (2020) are closely related to the present paper, although both feature RBC models with supply side shocks only. Atalay estimates a structural industry-level model with a generalized production function. He shows that the elasticities of substitution between production factors, between intermediate inputs from different industries and between the consumption of industry-level goods are important determinants of how strongly shocks propagate between industries. He identifies low elasticities which suggest complementarity between industry goods and imply that industry-specific shocks account for roughly a half of the fluctuations of the aggregate output.

Vom Lehn and Winberry (2020) is the only paper which also examines the vanishing cyclicality of productivity in the U.S. in the mid-1980s using the industry approach. They find that the industries which act as suppliers of the investment goods are important drivers of the aggregate fluctuations and that idiosyncratic shocks to these industries generate countercyclical movement in aggregate measured productivity. Since the relative importance of the shocks to these industries has increased in the recent decades, their model generates the decrease in the cyclicality of productivity. Such explanation is complementary to ours as their model completely abstracts from the demand-side shocks. The vanishing cyclicality of productivity in vom Lehn and Winberry relies on the assumption of the decreasing returns to scale, which is not present in our model.

The main point in which we deviate from the existing literature is our focus on the identification of demand versus supply side shocks. We construct a New Keynesian model and include shocks with characteristics typical for each side. We indeed find that our aggregate demand shocks are the key driver of the aggregate fluctuations. Second, we allow for endogenous factor utilization formalized as workers' effort, which is not observable by the econometrician. The approach is based on the empirical work of Basu et al. (2006), who estimate the contribution of factor utilization and true technology shocks for the U.S. industries. The factor utilization channel is important, because it allows the model to generate variation in the measured productivity without exogenous shocks to technology. Several of the models in the literature (Foerster et al. 2011, Atalay 2017, etc.) conclude that the aggregate technology shocks are important drivers of business cycle fluctuations because such shocks are basically the only shocks able to generate substantial co-movement in the measured productivity across industries. Hence, throughout this paper, we rigorously distinguish between exogenous shocks to *technology* and observable *measured productivity*.

The substantial decrease in the cyclicality of measured productivity in the U.S. in the mid-1980s has been documented by a number of papers starting from Stiroh (2009), Galí and Gambetti (2009) with further important empirical insights in Fernald and Wang (2016). The studies have documented a robust decline in the correlations between measured aggregate productivity and aggregate output, resp. production inputs across the two time periods: first, the post-war period between 1950 and the mid-1980s which we refer to as *pre-1984* period and second, the *post-1984* period from 1984 up to 2015, where the end date depends on data availability. Various explanations have been proposed by the rich theoretical and empirical literature, including Barnichon (2010), Galí and van Rens (2019), Lewis et al. (2018), Evans (2019), Berger

(2018), Riggi (2019), Garin et al. (2018) and others, see Molnárová (2020) for a discussion of the existing explanations.

Molnárová (2020) also points out the importance of industry-level evidence for discriminating between the various mechanisms that try to explain the vanishing cyclicality of productivity, since the change in the cyclicality is virtually non-existent at the level of individual industries. However, the existing explanations have qualitatively different implications for the industry-level moments. In this paper we focus on a mechanism that is able to generate a decrease in the procyclicality of measured productivity without generating counterfactual predictions at the industry level, which is the change in the structure of shocks, see Barnichon (2010), Foerster et al. (2011), Galí and Gambetti (2009). We find that our model generates a significant part of the decrease in the procyclicality of measured productivity observed in the U.S. when we change the composition of the shocks in line with the literature estimates for the post-1984 period.

Lastly, this paper is also related to the recent strand of literature that studies the propagation of shocks in industry-level New Keynesian models. The models in this literature are closely related to ours, but the papers have a different focus, concentrating mostly on the heterogeneity of industry-level inflation and transmission of monetary policy shocks. Bouakez et al. (2014), Pasten et al. (2017) and Pasten et al. (2018) point out the importance of heterogeneous price rigidity across industries, amplified through the input-output linkages. Bouakez et al. focus on a narrow selection of shocks, excluding the shock to aggregate technology and industry-specific demand shocks. They show that the heterogeneous response of prices across industries are per se very important for the transmission of the effects of the monetary policy. Smets et al. (2019) estimate a New Keynesian model using Bayesian techniques and find that the input-output linkages are the major source of heterogeneous inflation patterns across industries and that industry-level shocks contribute to aggregate inflation volatility.

2 Model

This section presents the New Keynesian DSGE model with production disaggregated at the industry level, featuring 77 industries which are linked via the input-output network. The model economy is subject to two types of aggregate shocks, one technology shock and one shock to aggregate demand. In addition, each industry is subject to idiosyncratic shocks to its technology and demand. The input-output network propagates the industry-specific shocks through the economy. We use the model to study the role of demand and supply side shocks in the fluctuations of industry-level and aggregate variables, with particular focus on measured productivity. Therefore, the model incorporates an endogenous factor utilization margin which creates a wedge between *measured total factor productivity* and exogenous *technological* improvements.

Because we model each industry individually, the model features a very large number of variables. We solve the model by linearization around the deterministic steady state.

2.1 Industries

Production in the model economy is organized into I different industries, indexed by $i = 1, \ldots, I$. The output of each industry has three potential purposes. It is used as a *consumption good* (cf. section 2.2), in the production of *investment goods* (section 2.4), or as an *intermediate input* in the production of firm output (section 2.3).

Each industry consists of a continuum of monopolistically competitive firms represented by the unit interval. The differentiated firm goods aggregate to industry output according to

$$y_{i,t} = \left(\int_0^1 y_{ki,t}^{\frac{\sigma_I - 1}{\sigma_I}} dk \right)^{\frac{\sigma_I}{\sigma_I - 1}}, \tag{1}$$

where $y_{ki,t}$ denotes the output produced by an individual firm k in industry i and $\sigma_I > 0$ is the elasticity of substitution between the firm goods. The aggregator 1 implies iso-elastic demand for goods of firm k:

$$y_{ki,t} = \left(\frac{p_{ki,t}}{p_{i,t}} \right)^{-\sigma_I} y_{i,t}. \tag{2}$$

Here $p_{ki,t}$ is the price set by firm k, and $p_{i,t}$ is the price index of industry i, given by

$$p_{i,t} = \left(\int_0^1 p_{ki,t}^{1-\sigma_I} dk \right)^{\frac{1}{\sigma_I - 1}}. \tag{3}$$

2.2 Households

The economy is populated by a continuum of infinitely-lived representative households. Households provide labor input, consume goods, save in the form of bonds and capital, and receive all firm profits. The objective of the representative household is to maximize

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(C_t - \chi \bar{C}_t) - \frac{N_t^{1+1/\sigma_U}}{1 + 1/\sigma_U} \right], \tag{4}$$

where C_t are units of a bundle of consumed goods and the term $\chi \bar{C}_t$ represents consumption habits that are assumed to be external to the individual household, $\bar{C}_t = C_{t-1}$. N_t is an index of the labor services provided to various industries and σ_U is the corresponding elasticity of the total labor supply.

The consumption bundle is a composite of differentiated industry goods

$$C_t = \left(\sum_{i=1}^{I} v_{i,t}^{\frac{1}{\sigma_C}} c_{i,t}^{\frac{\sigma_C - 1}{\sigma_C}} \right)^{\frac{\sigma_C}{\sigma_C - 1}} \tag{5}$$

where $c_{i,t}$ is the amount of industry i good that is used for consumption, $v_{i,t}$ is the weight of that good in the consumption basket and $\sigma_C > 0$ is the elasticity of substitution between the industry goods. The weights are subject to exogenous variation over time, which we interpret as *shocks to relative industry demand*, specified in more detail in section 2.7. We normalize the shocks to relative demand such that their effect on the aggregate price level is neutralized up to a first order approximation.

The price P_t of a unit of the consumption bundle is defined so as to satisfy

$$P_t C_t = \sum_i p_{i,t}^{NOM} c_{i,t}, \tag{6}$$

where $p_{i,t}^{NOM}$ is the nominal price of industry good i. Expressing industry-prices relative to the price of consumption bundle, $p_{i,t} = p_{i,t}^{NOM}/P_t$, the iso-elastic demand function for goods of industry i is given as

$$c_{i,t} = {v_{i,t}}^{\sigma_C} {p_{i,t}}^{-\sigma_C} C_t. \tag{7}$$

Equations 6 and 7 imply that the relative prices satisfy

$$1 = \left(\sum_{i=1}^{I} v_{i,t} {p_{i,t}}^{1-\sigma_C} \right)^{\frac{1}{1-\sigma_C}}. \tag{8}$$

The utility function 4 states that households draw negative utility from providing an index N_t of labor services to various industries. The labor supply index is given by

$$N_t = \left(\sum_{i=1}^{I} \eta_i g(h_{i,t}, e_{i,t})^{\frac{\sigma_N+1}{\sigma_N}} \right)^{\frac{\sigma_N}{\sigma_N+1}}. \tag{9}$$

The disutility depends on the number of differentiated hours $h_{i,t}$, as well as the effort $e_{i,t}$ exerted by the workers in each industry. Workers' effort is a measure of performance that we assume is observed and remunerated by firms, but not observed in the data.

Similar to Horvath (2000) and Bouakez et al. (2014), household preferences over working in different industries are given by the weight parameters η_i and the elasticity parameter $\sigma_N > 0$. The latter determines how elastically the industry labor supply allocation reacts to changes in industry wages. For σ_N approaching infinity, labor inputs in various industries are perfect substitutes as far as the household is concerned. For $\sigma_N < \infty$, households prefer to diversify their labor input, thus the labor input is not perfectly mobile across industries. This specification allows for industry-specific wages in our representative household framework.

Finally, the function g describes household preferences over hours and effort. Utility is decreasing in both hours and effort supplied to each industry according to

$$g(h_{i,t}, e_{i,t}) = \left(\frac{{h_{i,t}}^{\sigma_h}}{\sigma_h} + \Lambda_i \frac{{e_{i,t}}^{\sigma_e}}{\sigma_e} \right)^{\frac{\sigma_h+\sigma_e}{\sigma_h \sigma_e}}, \tag{10}$$

where the parameters $\sigma_h \geq 0$ and $\sigma_e \geq 0$ determine the elasticity with which households adjust the supply of hours and effort, respectively, and $\Lambda_i \geq 0$ is an industry-specific parameter. Notice that g is jointly convex in hours and effort.

The total labor service available to the firms in industry i is the product of hours and effort,

$$l_{i,t} = e_{i,t} h_{i,t}. \tag{11}$$

Firms pay the wage $w_{i,t}$ per unit of labor service $l_{i,t}$ and the household can choose hours and effort optimally, such that the disutility of providing labor services $l_{i,t}$ is minimized, cf. Barnichon

(2010). Household first order conditions imply

$$e_{i,t} = \Lambda_i^{-\frac{1}{\sigma_e}} h_{i,t}^{\frac{\sigma_h}{\sigma_e}}. \tag{12}$$

Hence, there is a monotone relationship between hours and effort. Models with endogenous factor utilization often imply that it is optimal to adjust various input margins simultaneously, see Basu et al. (2006). This property of the model is useful, because in the data hours are observed but effort is not. The elasticity of effort response relative to that of hours only depends on the ratio of the parameters σ_h/σ_e. Without loss of generality, we normalize σ_h to one in all quantitative exercises. The higher the value of parameter σ_e, the less effort fluctuates in comparison to hours. Moreover, notice that as an immediate implication of equation 12, the function g is linear in labor input l_i.

With all prices expressed in terms of the consumption bundle, the budget constraint of the household is given by

$$\left(\sum_{i=1}^{I} w_{i,t} l_{i,t}\right) + r_t^k K_{t-1} + T_t + B_{t-1} r_t^b = C_t + P_t^X X_t + B_t, \tag{13}$$

where $w_{i,t}$ are real industry-specific wages per unit of labor input, K_t is capital stock at the end of period t, r_t^k is gross real return on capital, T_t are aggregate firm profits, X_t is gross investment and P_t^X is the real price of investment good.

Besides physical capital, the household can also save in the form of a one-period riskless bond, B_t. The bond yields the real return

$$r_t^b = D_{t-1} \frac{R_{t-1}}{\pi_t}, \tag{14}$$

where the nominal interest rate R_t is set by the monetary authority, and π_t is consumer price inflation. We interpret the exogenous disturbance term D_t as the aggregate demand shock. The shock represents a wedge between the nominal interest rate set by the monetary authority and the interest rate available to the household. This type of demand shock is used in the recent DSGE literature, for example Smets and Wouters (2007), where it is referred to as the *risk premium shock*.

2.3 Firms

In each industry, firms act under monopolistic competition and produce goods using capital and labor services as well as intermediate inputs. Firms maximize the expected discounted value of their future profits.

All firms in an industry have access to the same technology and are the same ex ante. Therefore, in order to simplify the formulas, we omit firm indices in the following firm-level equations. The gross output of a firm in industry i follows

$$y_{i,t} = A_t z_{i,t} \left[\mu_{i,K}^{\frac{1}{\sigma_y}} k_{i,t}^{\frac{\sigma_y - 1}{\sigma_y}} + \mu_{i,L}^{\frac{1}{\sigma_y}} l_{i,t}^{\frac{\sigma_y - 1}{\sigma_y}} + \mu_{i,M}^{\frac{1}{\sigma_y}} M_{i,t}^{\frac{\sigma_y - 1}{\sigma_y}} \right]^{\frac{\sigma_y}{\sigma_y - 1}} - \Phi_i, \tag{15}$$

where A_t is exogenous stochastic aggregate technology that affects all the industries. In contrast, $z_{i,t}$ is a technology process that only affects firms in industry i. The production factors capital $k_{i,t}$, labor $l_{i,t}$, and intermediate inputs $M_{i,t}$ are combined with elasticity of substitution $\sigma_y > 0$. The weights $\mu_{i,\times}$ determine the relative importance of the production factors. The intermediate input composite $M_{i,t}$ is produced from industry goods with a constant returns to scale technology

$$M_{i,t} = \left(\sum_{j=1}^{I} \alpha_{ji}^{\frac{1}{\sigma_M}} m_{ji,t}^{\frac{\sigma_M - 1}{\sigma_M}} \right)^{\frac{\sigma_M}{\sigma_M - 1}},$$

where $m_{ji,t}$ denotes the intermediate good from industry j that a firm in industry i uses to produce its output. The parameter $\sigma_M > 0$ is the elasticity of substitution between intermediate inputs from different industries. The weights $\alpha_{ji} \geq 0$ determine the relative importance of intermediate inputs from various industries.

In order to produce, firms in industry i must pay a fixed cost $\Phi_i \geq 0$. Because of the fixed cost, the firms face increasing returns to scale in net output and changes in demand generate changes in measured productivity. Next to endogenous factor utilization, fixed costs are another reason why changes in measured productivity are different from exogenous technological changes.

The firms are subject to nominal price rigidities of the Calvo-type. Since the firms in industry i are ex ante identical, they all choose the same optimal price $p^*_{i,t}$ conditional on adjusting. Substituting into 3, the price index of the good of industry i evolves according to

$$p_{i,t} = \left[\theta_i \left(\frac{p_{i,t-1}}{\pi_t} \right)^{1-\sigma_I} + (1-\theta_i) {p^*_{i,t}}^{1-\sigma_I} \right]^{\frac{1}{1-\sigma_I}}, \tag{16}$$

where $\theta_i \in [0,1]$ is the probability that a firm is not allowed to adjust the price in period t. As discussed amongst others in Bouakez et al. (2014), the degree of price stickiness is likely to differ across industries. However, the identification of the parameter θ at the industry level is difficult. Therefore, we use the same degree of price stickiness across all industries in the benchmark calibration, and check for robustness using the parameters θ_i identified by Bouakez et al. (2014).

The problem of a representative firm at time t is to choose the amount of capital, labor, intermediate inputs, and price of its good (if possible) in order to maximize the value of expected future profits. In nominal terms, the dynamic price-setting problem of the firms is to maximize

$$\mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s} \left[y_{i,t+s|t} p^{NOM}_{i,t} - \mathcal{C}_{i,t+s|t} \right], \tag{17}$$

where $p^{NOM}_{i,t}$ is the nominal price set at time t and $y_{i,t+s|t}$ is period $t+s$ demand for goods of a firm in industry i that was last setting its prices in period t. $Q_{t,t+s}$ is nominal stochastic discount factor between periods t and $t+s$, defined as

$$Q_{t,t+s} = \beta^s \frac{\lambda_{t+s}}{\lambda_t} \frac{P_t}{P_{t+s}},$$

where λ_t denotes the marginal utility of consumption at period t. $\mathcal{C}_{i,t+s|t}$ are the firm nominal costs of producing output $y_{i,t+s|t}$. Apart from the fixed costs, the production is constant returns to scale. Thus, we can express the nominal costs in terms of the real marginal costs $RMC_{i,t}$ as

$$\mathcal{C}_{i,t+s|t} = P_{t+s} RMC_{i,t+s} (y_{i,t+s|t} + \Phi_i),$$

where the real marginal costs are given by

$$RMC_{i,t} = \frac{1}{A_t z_{i,t}} \left(\mu_{i,K} {r_t^k}^{1-\sigma_y} + \mu_{i,L} {w_{i,t}}^{1-\sigma_y} + \mu_{i,M} {P_{i,t}^M}^{1-\sigma_y} \right)^{\frac{1}{1-\sigma_y}}. \tag{18}$$

In the absence of nominal rigidities, profit maximization of the firms implies a price markup of $\frac{1}{\sigma_I - 1}$ over the marginal costs.

2.4 Investment and capital

Investment into physical capital uses the specialized investment good X. The amount of X_t produced is given by

$$X_t = \left(\sum_{i=1}^{I} {\xi_i}^{\frac{1}{\sigma_X}} {x_{i,t}}^{\frac{\sigma_X - 1}{\sigma_X}} \right)^{\frac{\sigma_X}{\sigma_X - 1}},$$

where $x_{i,t}$ is the amount of industry-i good that is used in the production of the investment good, ξ_i gives the weight of industry-i good in production, and the parameter $\sigma_X > 0$ is the elasticity of substitution between industry goods. The demand for the good of industry i is iso-elastic, given by

$$x_{i,t} = \xi_i \left(\frac{p_{i,t}}{P_t^X} \right)^{-\sigma_X} X_t. \tag{19}$$

The price of the investment good relative to consumption follows from the relative prices of the industry goods as

$$P_t^X = \left(\sum_{i=1}^{I} \xi_i {p_{i,t}}^{1-\sigma_X} \right)^{\frac{1}{1-\sigma_X}}. \tag{20}$$

Capital is subject to adjustment costs formulated as in Hayashi (1982). The costs are quadratic in investment intensity ι_t, defined as

$$X_t = \iota_t K_{t-1}. \tag{21}$$

The aggregate capital stock evolves according to

$$K_t = (1-\delta) K_{t-1} + \phi(\iota_t) K_{t-1}. \tag{22}$$

Thus, for any investment intensity ι_t, the part $\phi(\iota_t) K_{t-1}$ that is added to the capital stock is given by

$$\phi(\iota_t) = \iota_t - \frac{(\iota_t - \delta)^2}{\kappa \delta},$$

where δ is rate of depreciation and κ is the parameter that determines the strength of the adjustment costs. This formulation of capital adjustment costs is equivalent to several other ways of introducing convex adjustment costs, cf. Wang and Wen (2010). While the aggregate capital stock in the model is rigid, there are no frictions to capital mobility across industries.

2.5 Monetary policy

Monetary policy follows a simple interest rate rule,

$$r_t = r^* + \gamma_r(r_{t-1} - r^*) + (1 - \gamma_r)\gamma_\pi(\pi_t - \pi^*). \tag{23}$$

Parameters r^* and π^* are the desired policy targets. Parameter $\gamma_r \geq 0$ determines the rigidity of the interest rate rule of the monetary authority. Parameter $\gamma_\pi > 1$ is the Taylor parameter that governs the strength with which the monetary authority reacts to the fluctuations of inflation.

2.6 Market clearing

All markets clear in equilibrium. In particular, for each industry good j, the total production equals the amount of good j used in the production of final good, investment good, and intermediate inputs to production in all industries

$$y_{j,t} = c_{j,t} + x_{j,t} + \sum_{i=1}^{I} m_{ji,t}. \tag{24}$$

2.7 Exogenous shocks

There are four types of exogenous structural shocks in our model. Two aggregate processes drive the aggregate technology A_t and the risk premium wedge D_t. Two types of industry-specific processes drive the industry technology $z_{i,t}$ and the relative demand for industry goods $\tilde{v}_{i,t}$. We assume that each shock follows an AR(1) process.

- Aggregate technology follows

$$\log(A_t) = \rho^A \log(A_{t-1}) + \epsilon_t^A, \qquad \epsilon_t^A \sim \mathcal{N}(0, \sigma_A^2) \tag{25}$$

- The risk premium shock follows

$$\log(D_t) = \rho^D \log(D_{t-1}) + \epsilon_t^D, \qquad \epsilon_t^D \sim \mathcal{N}(0, \sigma_D^2) \tag{26}$$

- The technology of industry i follows

$$\log(z_{i,t}) = \rho^z \log(z_{i,t-1}) + \epsilon_{i,t}^z, \qquad \epsilon_{i,t}^z \sim \mathcal{N}(0, \sigma_{z,i}^2) \tag{27}$$

- The relative demand for goods of industry i is normalized such that $\sum_{i=1}^{I} v_{i,t} = 1$ in each period,

$$v_{i,t} = \tilde{v}_{i,t} / \sum_{i=1}^{I} \tilde{v}_{i,t}. \tag{28}$$

The exogenous processes $\tilde{v}_{i,t}$ follows

$$\log(\frac{\tilde{v}_{i,t}}{\nu_i}) = \rho^v \log(\frac{\tilde{v}_{i,t-1}}{\nu_i}) + \epsilon^v_{i,t}, \qquad \epsilon^v_{i,t} \sim \mathcal{N}(0, \sigma^2_{v,i}). \tag{29}$$

Since these four types of shocks play a central role in our analysis, let us briefly discuss their interpretation. We view the aggregate demand shock in the form of the risk premium wedge as a proxy for a variety of demand-side shocks. Demand-side shocks are typically characterized as disturbances that generate positive correlation between aggregate consumption, investment, output, and the price level. The risk premium wedge shares these characteristics and is similar in effect to several other shocks standard in the literature, such as monetary policy shocks, discount factor shocks, financial intermediation shocks and others.

The (positive) demand shock to industry i is characterised such that for a given level of prices, consumers prefer to consume more of good i, at the expense of the goods of other industries. As a consequence, the relative price of this good tends to rise, contrary to the industry-level technology shock. In the data, however, the increased demand might be a consequence of an increase in the quality of good i, in the case this is not correctly accounted for by the statistical office. Since our model can not distinguish between shifts in preferences and unaccounted quality improvements, it would identify both cases as demand shocks.

We model the technology process for individual industries as a combination of independent industry technology shocks and a common aggregate technology shock. In fact, the correlations between the technology processes across different industries might have a much more general structure. However, it is not possible to identify the general variance-covariance matrix using the short data series that we have available.[2]

2.8 Measurement errors

Hours in the model are subject to measurement errors. It is widely recognized that measuring hours worked is difficult, as it relies on survey information or administrative data, both of which are connected to well known issues, see e.g. Heathcote et al. (2014), Blundell et al. (2016). Moreover, adding the measurement errors also helps to bring the model closer to the data. Our model is quite parsimonious in terms of number of shocks, and as a consequence tends to generate too strong co-movement between variables. Measurement error shocks systematically reduce the correlations in the model, bringing them closer to the data.

In line with how we specified the rest of the shocks, the measurement error shock has an aggregate and an industry-specific component. We assume that measured hours in each industry follow

$$\log(h^m_{i,t}) = \log(h_{i,t}) + \epsilon^{ME}_{i,t} + \epsilon^{aME}_t, \tag{30}$$

where $\epsilon^{ME}_{i,t}$ is the idiosyncratic industry-level measurement error and ϵ^{aME}_t is the aggregate measurement error. We assume that measurement error shocks are i.i.d. normally distributed. Notice that, by affecting measured hours, the measurement errors indirectly affect measured labor productivity and measured total factor productivity as well.

[2]The estimated correlation matrix from a collection of T data points of n variables has rank smaller than or equal to $T-1$. We work with 77 industries and the sample is 46 years, 25 in the pre-1984 subperiod.

2.9 Transmission of shocks between industries

Finally, we briefly describe the channels of transmission of the industry-specific shocks between industries in our model. These are similar to the mechanisms described in the existing literature (cf. section 1.1), apart from some modifications that arise because of nominal rigidity. The intuition is based on equation 18, which expresses the real marginal costs of an optimizing firm, and equation 7, which expresses the optimal demand for consumption of industry i good given its price.

The responses of the firms in industry i to shocks in their own industry are straightforward: a positive shock to technology drives down the real marginal costs, pushing down the prices of industry i's goods. A positive shock to demand in industry i increases the output of that industry, which creates an upward pressure on the prices of the industry's inputs and, subsequently, output. However, the price effect is relatively small, as the movement of production factors across industries in our model is relatively flexible. Even after a demand shock, measured productivity increases, due to the endogenous labor utilization and fixed costs.

A positive shock to technology in an upstream industry j, which provides either intermediate inputs or investment goods to sector i, decreases the real marginal costs in sector i, creating a negative pressure on its prices and boosting the output. Thus, output and measured productivity in sector i co-move with sector j. This channel has been thoroughly studied in the literature. In the New Keynesian model with price rigidities, the mechanism is somewhat dampened in comparison to the RBC setup where all prices adjust instantly. In contrast, a positive shock to demand in the upstream industry j has an adverse effect on industry i. As prices of industry j good increase with higher demand, industry i also faces higher input prices. Thus, its output and productivity fall.

Transmission of the shocks also happens in the opposite direction, from downstream industries upwards. A positive shock to demand in the downstream industry k, which buys intermediate inputs or investment goods from industry i, increases industry k's demand for production factors, effectively increasing the demand for goods of upstream industry i as well. Thus, the demand shock generates a positive co-movement between industries k and i. For a positive technology shock in downstream industry k, on the other hand, the effect on industry i is ambiguous in the short run. Due to the rigid prices, the demand for goods of industry k is quasi-fixed in the short run. Thus, the demand for production factors in industry k falls on impact, suppressing output and productivity in industry i. Later, as more and more firms in industry k are able to adjust their prices, the demand for industry k good grows, with the demand for industry i good also recovering.

3 Data and calibration

3.1 Data sources

The primary data source is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and

2005 disaggregated into 88 industries. The data set is unique in that it provides complete industry input-use tables including the corresponding price data for each year within the sample period. The annual tables provide the information necessary for calibrating the substitution elasticities in production and household demand. Additionally, we supplement the data set with the information from the BEA capital-flow table and the BEA input-use table (both 1992) to calibrate industry weights in investment and final consumption, respectively.

We focus on the private business sector which consists of 77 industries. We use the standard bottom-up KLEMS methodology in order to construct the aggregate series from the industry-level data, see e.g. Timmer et al. (2007). The list of the industries, as well as the details describing the construction of data series and the moments are provided in appendix B.

3.2 Measured productivity and output

The key to our analysis is the understanding of the various concepts of productivity as they are commonly used in the literature. Our model features a factor utilization margin, which is not observed in the data, fixed costs of production, firm profits and measurement errors. As a consequence, the standard Solow residual measures used in productivity accounting deviate from the exogenous technology in the model. At firm level, computing the Solow residuals following the methodology of the EU KLEMS database leads to

$$\hat{TFPm}_{i,t} = \hat{y}_{i,t} - s^K_{i,t}\hat{k}_{i,t} - s^L_{i,t}\hat{h}^m_{i,t} - s^M_{i,t}\hat{M}_{i,t}, \tag{31}$$

where s^X denotes the cost share of input X on gross output and hats denote growth rates of variables. We refer to residual $TFPm$ as the *measured productivity (TFP)*. On the other hand, the firm-level exogenous technology can be expressed in our model as

$$\hat{TFP}_{i,t} = \hat{A}_t + \hat{z}_{i,t} = \frac{y_{i,t}}{y_{i,t} + \Phi_i}\left[\hat{y}_{i,t} - \mu_{i,t}(s^K_{i,t}\hat{k}_{i,t} - s^L_{i,t}(\hat{h}_{i,t} + \hat{e}_{i,t}) - s^M_{i,t}\hat{M}_{i,t})\right], \tag{32}$$

where Φ_i is the fixed cost and $\mu_{i,t}$ is the effective markup over the marginal costs.

Expressions 31 and 32 are only equal if the fixed costs are zero, prices are perfectly competitive, workers effort is constant over time and hours are measured precisely. Measured productivity reflects exogenous technology, but also fluctuations due to the unobserved effort, returns to scale and markups.

While we can easily distinguish the two measures of productivity in the model, it is very difficult to identify the *true* technology process $TFP_{i,t}$ in the data. The effective markup $\mu_{i,t}$, fixed costs Φ_i, and workers effort $e_{i,t}$ are not observable. Both inputs and output are subject to measurement issues. The data set reports the remuneration of production factors, but the capital share is pinned down as the residual. Therefore, firm profits are also included in the reported capital shares $s^K_{i,t}$.

Industry-specific real value added is defined in line with the growth accounting methodology in terms of growth rates as

$$\hat{va}_{i,t} = \frac{1}{s^{VA}_{i,t}}\left(\hat{y}_{i,t} - s^M_{i,t}\hat{M}_{i,t}\right), \tag{33}$$

and aggregate real value added follows the same definition using aggregate real gross output and aggregate intermediate inputs. Because the model abstracts from taxes, gross domestic product equals aggregate value added.

In line with most of the literature, we construct the growth rates of *aggregate measured productivity (TFP)* according to the KLEMS methodology using aggregate inputs and output[3]

$$\hat{TFPm}_t = \hat{VA}_t - s_t^K \hat{K}_t - s_t^L \hat{H}_t, \tag{34}$$

where s^K, s^L denote the cost share of capital resp. labor on value added, VA_t is aggregate value added, K_t is the aggregate capital and H_t are the aggregate hours. When comparing the data with the model-generated series, we compute measured productivity in the same way in both cases, using equations 31 and 34.

One should recognize that measures of productivity based on Solow residuals may reflect unobserved fluctuations in production inputs other than effort, most importantly composition effects and changes in capital utilization. Our data set is to some extent adjusted for endogenous variation in labor and capital composition. The measure of labor input reported in the data set is effective hours, defined as total hours adjusted for the composition of workforce, taking into account workers' education, age, and gender.

3.3 Calibration

We formulate the model at quarterly frequency and aggregate the simulated series to annual frequency in order to compare the model to our annual data. The baseline calibration aims to reflect the U.S. economy over the period 1960-1984. We provide additional details on the calibration procedure in appendix B and robustness checks in appendix C.

Where possible and appropriate, we set model parameters to standard values from the literature. Following most of the New Keynesian literature, we solve the model by linearization around the zero inflation steady state. The discount rate β is set such that the implied interest rate is 4% annually. The annual capital depreciation rate δ is 10%. The capital adjustment cost parameter κ is calibrated such that the volatility of investment generated by the model is about 3.3 times higher compared to output, in line with the empirical evidence. The elasticity of substitution between firm goods within the same industry σ_I is set to imply a 10% markup, which is within the standard range. We calibrate the fixed costs Φ_i such that the firms make zero profits in steady state. The Taylor rule parameters γ_π and γ_r are set to 1.5 and 0.8, respectively. In the baseline calibration, the price stickiness θ_i is set to 0.75 in each industry, implying the average price adjustment frequency once a year. We set the consumption habit parameter χ to 0.5, towards the lower end in the DSGE literature.

The combination of the labor input elasticity σ_U and the effort elasticity parameter σ_e determines the wage elasticity of hours comparable to the standard Frisch elasticity in aggregate macroeconomic models. The parameter σ_U is calibrated conditional on σ_e, such that the implied Frisch elasticity is 0.5, within the range considered in the literature. More information about the mapping between the model parameters and the Frisch elasticity can be found in appendix B.

[3] Our measure of aggregate TFP is value added-based, not gross output-based Solow residual. The difference between the two measures only affects the scaling of the productivity series.

The parameters of the model describing the industry-level structure of the economy are all chosen to match long-run averages in the data. In the production function, each of the intermediate input weights α_{ji} is set to match the long-run average cost share of intermediate inputs from industry j to industry i in the Jorgenson data set. The industry-specific factor weights $\mu_{K,i}$, $\mu_{L,i}$, and $\mu_{M,i}$ are set to match the industry i's cost shares of capital, labor, and intermediate inputs, again using the long-run averages from the Jorgenson data set. The investment good composition weights ξ_i are set to match the cost shares of investment from the 1992 BEA capital-flow table. As the model only features one type of investment, we use the average composition across all industries to calibrate weights ξ_i. Regarding the household preferences, the consumption composition weights ν_i are set to match the cost shares of consumption from the 1992 BEA input-use table. The industry-specific preference parameters for supplying labor across different industries η_i are chosen such that in steady state, the allocation of labor supply across industries matches the long-run average industry composition in the data, conditional on average industry wages, cf. the intra-temporal labor supply first order condition 49.

The remaining parameters of the model consist of the substitution elasticities in the production process, consumption, and labor supply (σ_y, σ_M, σ_X, σ_C, σ_N and σ_e), the variances of the shocks to technology (σ_A^2 and $\sigma_{z,i}^2$), to demand (σ_D^2 and $\sigma_{v,i}^2$), and of the measurement error. Out of these parameters, the elasticities σ_y, σ_M are calibrated directly to match specific data targets, see the discussion below. The rest of the parameters are calibrated using indirect inference, within a two-step procedure which targets a relevant set of moments. In the inner loop of the procedure, we determine the variances of all shocks conditional on the elasticity parameters. The variances of the measurement error shocks are calibrated to generate an ex-ante given share of aggregate and industry fluctuations. The variances of the structural shocks are estimated using simulated method of moments. In the outer loop, the elasticities σ_X, σ_C, σ_N and σ_e are calibrated such that they jointly match a set of three moments with one additional identifying assumption.

Comparatively little attention has been given to estimating the elasticities of substitution between factor inputs and between industry-specific goods in the macro literature in recent decades, although they influence the way in which the economy responds to the various types of shocks, see Atalay (2017) for discussion. We believe that the calibration of the elasticities σ_y, σ_M, σ_C, σ_X, and σ_N is one of the useful contributions of our paper. Our model is parsimonious in that the elasticities are the same across all industries. Therefore, we have a relatively small set of parameters that we estimate using a large number of industry-level series in the outer loop. We choose the method of moments over maximum likelihood methods, because it allows a better interpretation of which data features determine the values of the individual parameters. Table 1 shows an overview of the model parameters and calibration targets.

3.3.1 Elasticities: identifying moments

In this section we briefly discuss which moments in the data identify the individual elasticity parameters. We calibrate the production function parameters σ_y and σ_M directly from the estimated elasticity of the corresponding input shares to the changes in the relative prices. For the elasticity of substitution between production factors σ_y, the first order condition 62 implies

Calibration summary			
Parameter	Symbol	Value	Target/Source
Elasticities			
Intra-industry substitution	σ_I	11	10% markup
Production factors subst.	σ_y	0.39	price elasticity of production factors
Intermediate inputs subst.	σ_M	0.75	price elasticity of intermediate inputs
Consumption good subst.	σ_C	0.38	price elasticity of industry gross output
Investment good subst.	σ_X	0.38	equals σ_C
Total labor input	σ_U	1.1	Frisch elasticity 0.5
Industry labor input subst.	σ_N	7.9	mean volatility of industry hours
Effort	σ_e	1.9	correlation productivity and hours
Hours	σ_h	1	normalization
Cost shares			
Production factor weights	$\mu_{i,\times}$		cost shares Jorgenson database, average
Intermediate inputs weights	α_{ji}		cost shares Jorgenson database, average
Consuption weights	ν_i		1992 BEA input-use table
Investment good weights	ξ_i		1992 BEA capital flow table
Fixed costs	Φ_i		zero profits in steady state
Shock processes			
Aggregate technology, volatility	σ_A		SMM objective
Industry technology, volatility	$\sigma_{z,i}$		SMM objective
Aggregate demand, volatility	σ_D		SMM objective
Industry demand, volatility	$\sigma_{v,i}$		SMM objective
Agg. measurement error, volatility	σ_{aME}		20% variance of agg. measured hours
Ind. measurement error, volatility	$\sigma_{ME,i}$		25% variance of ind. measured hours
Autocorrelation, structural shocks	$\rho^{\times}$	0.95	standard
Other			
Discount factor	β	0.96	standard (annual)
Capital depreciation	δ	10%	standard (annual)
Consumption habit	χ	0.5	standard
Taylor parameter	γ_π	1.5	standard
Taylor rule smoothing	γ_r	0.8	standard
Adjustment cost capital	κ	20	relative volatility of investment
Price stickiness	θ_i	0.75	standard
Industry weight labor disutility	η_i		industry hours/wages in steady state
Effort weight in labor disutility	Λ_i		normalization effort in steady state

Table 1: Calibration summary

that for each model industry i,

$$d\ln\left(\frac{M_{i,t}P^M_{i,t}}{l_{i,t}w_{i,t}}\right) = (\sigma_y - 1)d\ln\left(\frac{w_{i,t}}{P^M_{i,t}}\right). \tag{35}$$

We use the industry-level information about prices and volumes from the Jorgenson data set and regress the changes in the cost shares (left-hand side of equation 35) on the changes in the relative prices (right-hand side) industry by industry. We use the average across the I industry coefficients to pin down the value of σ_y.

For the elasticity of substitution between intermediate inputs from various industries σ_M, we use the same approach based on the first order condition 56. We compute the regression coefficient for each pair of intermediate inputs supplied into each production industry i. We use the average over all estimates to pin down the value of σ_M. The Jorgenson data set is unique in that it provides the information about the prices and volumes of the production inputs at the required level of disaggregation and across the longer time period. The values of σ_y and σ_M are broadly in line with the existing estimates, cf. Atalay (2017).

There are no model equations that directly map the remaining elasticity parameters σ_C, σ_X, σ_N and σ_e to the available data. Thus, these parameters are calibrated simultaneously in the outer loop of the calibration procedure using a set of three targets and one additional identifying assumption. However, each of the targeted moments identifies one of the parameters in an intuitive way. The parameters σ_C and σ_X both influence the reaction of the industry output shares to the changes in relative prices. As we do not have any information that distinguishes the impact of the two elasticities, we assume σ_C and σ_X are equal and target the average responsiveness of the relative industry output cost shares to relative prices. We target the statistic $\hat{\eta}^y$, computed as the average across industry-pair regression coefficients from the equation

$$d\ln\left(\frac{y_{i,t}p_{i,t}}{y_{j,t}p_{j,t}}\right) = \eta^y_{i,j} \cdot d\ln\left(\frac{p_{j,t}}{p_{i,t}}\right). \tag{36}$$

The elasticity of substitution between working in different industries σ_N influences the volatility of industry-level hours. We use the mean volatility of industry hours relative to the volatility of aggregate hours as the second target in the outer loop. The resulting value of $\sigma_N = 7.9$ implies high mobility of labour force across industries.

One of the essential elements of our model is the endogenous factor utilization. The elasticity of unobservable effort relative to hours is determined by parameter σ_e. A more elastic effort implies that measured productivity fluctuates more with hours and, everything else equal, the two variables are more correlated.[4] Thus, we identify σ_e by targeting the correlation between aggregate hours and measured productivity in the pre-1984 period. This is the only aggregate correlation that we target in the calibration procedure. The value of $\sigma_e = 1.9$ implies that for a one percent increase in hours worked, the effective labor input increases by roughly 1.5%, which is consistent with the existing literature. Basu et al. (2006) estimate that, including the factor utilization, a one percent increase in measured hours is associated with an increase of effective labor between 2.1% (nondurable manufacturing) and 0.64% (non-manufacturing industries).

[4] See Molnárová (2020) for discussion.

Relative standard deviations					
	Data	Industry shocks		Aggregate shocks	
		technology	demand	technology	demand
$\sigma(\hat{TFP}^m)/\sigma(\hat{VA})$	0.62	0.89	$\times$	0.93	0.48
$\sigma(\hat{H}^m)/\sigma(\hat{VA})$	0.83	0.26	$\times$	0.12	0.76
$\bar{\sigma}(\hat{tfp}_i^m)/\bar{\sigma}(\hat{y}_i)$	0.50	1.87	0.19	0.60	0.19
$\bar{\sigma}(\hat{y}_i)/\sigma(\hat{Y})$	1.96	1.87	15.2	1.16	1.13
$\bar{\sigma}(\hat{tfp}_i^m)/\sigma(\hat{TFP}^m)$	1.86	3.11	14.0	0.53	0.62

Table 2: Relative standard deviations of variables generated by each type of the shock separately. The first column shows the ratios of standard deviations measured in the data while columns 2 - 5 show the corresponding ratios generated by each type of shock in the model. For industry variables, $\bar{\sigma}(\cdot)$ denotes average across industry standard deviations. All variables are expressed in growth rates.

3.3.2 Shock variances

The main exercise of this paper is the estimation of variances of the exogenous shocks and their contribution to business cycle fluctuations. We jointly estimate the variances of the two aggregate shocks (σ_A^2 and σ_D^2) and two times I industry-specific shocks ($\sigma_{z,i}^2$ and $\sigma_{v,i}^2$) using the generalized simulated method of moments. We use three aggregate and $2 \times I$ industry-level variances in the SMM objective function. At the aggregate level, we target the variances of aggregate measured productivity, value added and hours. At the industry level, we target the variance of industry measured productivity and of industry gross output.[5] The resulting variances are the solution of a quadratic problem with inequality constraints, as all variances must be greater or equal to zero.

In order to provide some intuition on which data features identify the composition of the shocks in the model, we simulate the model four times, each time allowing for shocks of only one type. Table 2 displays the relative standard deviations for the set of variables that enter the SMM objective. The first column shows the data, while columns 2 - 5 report model simulations, each column generated by only one type of shock.[6] For the industry variables, the table reports simple averages of standard deviations across all industries.

The main insight from table 2 is that the different types of shocks generate different sets of second moments, such that the variances of the shocks are well identified. The relative importance of aggregate versus industry shocks is identified because the industry shocks generate higher volatilities of industry-level variables compared to the aggregate variables. This is not true for the aggregate shocks, cf. the last two rows of table 2. The volatility of the aggregate demand shock relative to technology shocks is pinned down by (each of) the first two rows of table 2. The first line shows that technology shocks, both on the aggregate and the industry level, generate fluctuations in aggregate measured productivity of almost the same size as that of aggregate value added, while the aggregate demand shock generates much smaller relative fluctuations. The second line displays the relative standard deviation of aggregate hours. In this case it is the demand shocks that generate large fluctuations, while technology shocks do very

[5]Notice that we do not include the variance of industry-level hours. The choice of the elasticity parameter σ_N in the outer loop pins down their average variance.

[6]In the case of industry shocks, we keep the variances of shocks across industries the same as in our baseline calibration.

little.[7] Thus, in order to match the relative volatilities of the aggregate variables, the model clearly needs aggregate demand shocks. Subsequently, as the relative size of aggregate demand shocks is determined by the relative volatilities of the aggregate variables, the information in the last two rows pins down the weight of the aggregate shock to technology relative to the industry-specific shocks. Lastly, the relative importance of the two industry-level shocks follows from the relative size of industry-level fluctuations in measured productivity and output, which is shown in the third row. Besides the three relative shock variances determined by the information in table 2, the absolute size of fluctuations is pinned down by the size of the fluctuations in the data.

One should point out that for industry variables, table 2 displays average standard deviations across all industries. In fact, we estimate the industry shock variances separately for each industry. Nevertheless, the identification logic described above works analogously for each industry individually. Due to the over-identification in the SMM procedure and the non-negativity constraint on variances, the targets are not matched precisely.

The variances of the measurement errors are calibrated to generate given shares of aggregate and industry measured hours, for discussion see e.g. Boivin and Giannoni (2006), Justiniano et al. (2013). The measurement errors are set to explain 20% of the variance of the aggregate hours and 25% of the variance of the industry hours. The measurement error shocks are not essential for our main results, namely that there are no aggregate technology shocks and that cyclicality of aggregate measured productivity decreases with smaller aggregate demand shocks. However, omitting the measurement error increases the co-movement between variables above what we observe in the data, see robustness checks in appendix C.

3.3.3 Alternative calibration for post-1984 period

The baseline model calibration targets the data moments from the pre-1984 period. In the second exercise we change the variance of the aggregate demand shocks and compare the model results to the data in the period after 1984. This is motivated by the fact that several authors, for example Barnichon (2010) and Galí and Gambetti (2009), have suggested that the great moderation period was characterised by a different composition of shocks, especially stressing the smaller shocks to aggregate demand, or muted effects of these shocks on the economy. We keep the rest of the parameters, including the variances of the other shocks, the same as in the baseline. This is because the aim of the exercise is to show to which extent a decrease in the volatility of the aggregate demand shocks can explain the changes in the co-movement patterns observed after 1984. It is not our ambition to precisely identify the decrease in the volatility of the aggregate demand shocks.

In order to pin down the alternative variance of the aggregate demand shock, we notice that the shock composition in the model has strong implications for the correlation between the aggregate hours and value added. Decreasing the volatility of the aggregate demand shock reduces this correlation. We choose this moment to discipline the exercise and decrease the variance of the shock such that the implied reduction in the correlation between the aggregate hours and value added is 17 p.p., which equals the reduction between the pre- and post-1984 samples in

[7] The weak response of hours to tech shocks is typical for New Keynesian models, see e.g. Galí (1999).

the data. Using this criterion, the volatility σ_D decreases by around 40%, in line with the change identified in the existing literature; see e.g. Barnichon (2010). As a further evidence that this decrease in volatility of the aggregate shock σ_D is reasonable, we observe that the alternative calibration generates a reduction in the standard deviation of value added from the pre-1984 value of 0.026 to the post-1984 value of 0.017, which is very close to the data.

4 Results

4.1 Model fit

In this section we show that the baseline calibration of the model fits the data very well in many dimensions. Tables 3, 4 and 5 compare sets of second moments in the data and generated from the model simulations. We mark the moments that we directly or indirectly used as calibration targets in bold. As the number of targets is bigger than the number of free parameters, the targets are not necessarily matched exactly. The top panel of each table displays the results for the baseline calibration and compares them to the data for pre-1984 period. The bottom panels show the results for the post-1984 period, which we discuss in section 4.5.

The top panel of table 3 displays standard deviations of aggregate variables relative to aggregate value added (or GDP), as well as their correlations with value added and with measured productivity. Our model provides a good match for all aggregate moments, with one notable exception. The model generates highly procyclical inflation, i.e., a strong Phillips curve characteristic for New Keyesian models. In contrast, inflation is basically acyclical in the data, which contain the stagflation period of the 1970s.

Table 4 summarizes the same information at the industry level. As the moments vary across industries both in the model and in the data, we report weighted averages of the second moments across the industries. The top panel of table 4 shows that the model fit is satisfactory at the industry-level as well. Average correlations of the industry variables with value added and measured productivity are well in line with the data for all variables. Average relative standard deviations are close to their data counterparts, once again with one exception. The volatility of prices at the industry level is substantially higher in the data than in the model. The possible explanations are that the model is missing pricing (markup) shocks, or that it does not reflect the measurement error in price data. The alternative version of the model with flexible prices, which we discuss in section 4.4, demonstrates that the low volatility of industry prices is not just a consequence of price rigidity in the model. Despite of the low volatility, the negative correlation between relative prices and value added at the industry level is an important confirmation that the model features a reasonable ratio of demand and supply-side shocks at the industry level.

Lastly, table 5 documents the co-movement between industries. For each industry-level variable we compute a correlation between each pair of industries. The table reports the unweighted mean of these 2926 pairwise correlations. The model does a good job in matching the average cross-industry correlations of most variables. The co-movement in the intermediate inputs used by the industries is slightly exaggerated. As a consequence, gross output across industries also

Aggregate variables: second moments									
	Standard dev. relative to value added*			Correlations with value added			Correlations with measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Baseline calibration									
Value added	*0.027*	(0.00)	***0.026***	1.00	(0.00)	1.00	0.85	(0.06)	0.87
Gross output	1.17	(0.05)	1.32	0.98	(0.00)	0.98	0.80	(0.08)	0.82
Measured TFP	0.62	(0.03)	**0.59**	0.85	(0.06)	0.87	1.00	(0.00)	1.00
Hours	0.83	(0.07)	**0.81**	0.86	(0.03)	0.83	0.49	(0.12)	**0.49**
Intermediate inputs	1.37	(0.09)	1.68	0.95	(0.01)	0.95	0.74	(0.08)	0.77
Inflation	0.93	(0.08)	1.01	0.14	(0.17)	0.92	-0.11	(0.24)	0.72
Labor productivity	0.51	(0.05)	0.54	0.56	(0.13)	0.58	0.89	(0.03)	0.88
Int. inputs per hour	0.77	(0.05)	1.04	0.76	(0.03)	0.88	0.80	(0.03)	0.87
Investment	-	-	3.29	-	-	0.97	-	-	0.83
Consumption	-	-	0.35	-	-	0.66	-	-	0.64
True TFP	-	-	0.27	-	-	0.18	-	-	0.40
Post-1984 calibration									
Value added	*0.016*	(0.00)	*0.017*	1.00	(0.00)	1.00	0.47	(0.18)	0.80
Gross output	1.20	(0.13)	1.25	0.90	(0.02)	0.96	0.26	(0.23)	0.71
Measured TFP	0.72	(0.07)	0.72	0.47	(0.18)	0.79	1.00	(0.00)	1.00
Hours	1.25	(0.20)	0.87	0.70	(0.04)	**0.66**	-0.26	(0.16)	0.11
Intermediate inputs	1.62	(0.25)	1.58	0.74	(0.07)	0.89	0.07	(0.23)	0.61
Inflation	1.51	(0.19)	0.93	0.11	(0.08)	0.82	0.05	(0.22)	0.51
Labor productivity	0.90	(0.13)	0.77	0.14	(0.17)	0.53	0.89	(0.01)	0.92
Int. inputs per hour	1.08	(0.12)	1.10	0.29	(0.17)	0.74	0.41	(0.10)	0.79
Investment	-	-	3.18	-	-	0.95	-	-	0.73
Consumption	-	-	0.44	-	-	0.66	-	-	0.62
True TFP	-	-	0.40	-	-	0.40	-	-	0.59

Table 3: Comparison of selected second moments in the model and in the data, growth rates of aggregate variabes. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. The values that are targeted in the calibration procedure are marked in bold. Bootstrapped standard errors (SE).
*except of standard deviation of value added.

Industry variables: averages across second moments									
	Standard dev. relative to value added*			Correlations with value added			Correlations with measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Baseline calibration									
Value added	*0.088*	(0.01)	*0.074*	1.00	(0.00)	1.00	0.78	(0.01)	0.81
Gross output	0.71	(0.00)	0.84	0.84	(0.01)	0.88	0.57	(0.01)	0.55
Measured TFP	0.36	(0.01)	0.38	0.78	(0.01)	0.81	1.00	(0.00)	1.00
Hours	0.56	(0.02)	**0.60**	0.38	(0.02)	0.46	-0.02	(0.03)	-0.06
Intermediate inputs	0.83	(0.01)	0.92	0.35	(0.04)	0.58	0.14	(0.02)	0.18
Prices	0.66	(0.03)	0.25	-0.33	(0.01)	-0.36	-0.43	(0.02)	-0.54
Input prices	0.33	(0.04)	0.11	-0.13	(0.02)	-0.15	-0.16	(0.02)	-0.21
Labor productivity	0.95	(0.04)	0.86	0.72	(0.01)	0.72	0.84	(0.01)	0.94
Int. inputs per hour	0.73	(0.02)	0.52	0.17	(0.04)	0.48	0.22	(0.04)	0.38
True TFP	-	-	0.36	-	-	0.44	-	-	0.73
Post-1984 calibration									
Value added	*0.097*	(0.01)	*0.070*	1.00	(0.00)	1.00	0.76	(0.03)	0.79
Gross output	0.47	(0.00)	0.79	0.84	(0.00)	0.87	0.53	(0.03)	0.51
Measured TFP	0.30	(0.01)	0.40	0.76	(0.03)	0.79	1.00	(0.00)	1.00
Hours	0.43	(0.01)	0.59	0.28	(0.02)	0.36	-0.23	(0.04)	-0.20
Intermediate inputs	0.58	(0.03)	0.84	0.43	(0.01)	0.50	0.12	(0.03)	0.06
Prices	0.83	(0.19)	0.26	-0.41	(0.01)	-0.38	-0.46	(0.01)	-0.54
Input prices	0.25	(0.03)	0.11	-0.10	(0.03)	-0.14	-0.11	(0.04)	-0.20
Labor productivity	1.03	(0.13)	0.91	0.68	(0.03)	0.73	0.90	(0.01)	0.95
Int. inputs per hour	0.52	(0.02)	0.47	0.20	(0.02)	0.37	0.34	(0.02)	0.33
True TFP	-	-	0.38	-	-	0.49	-	-	0.75

Table 4: Comparison of selected second moments in the model and in the data, growth rates of industry variables. Reported numbers are averages (weighted by industry output) across industry moments. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. The values that are targeted in the calibration procedure are displayed in bold. Bootstrapped standard errors (SE).
*except of standard deviation of value added.

Cross-Industry Correlations			
	Data	(SE)	Model
Baseline calibration			
Value added	0.14	(0.009)	0.13
Gross output	0.22	(0.015)	0.30
Measured TFP	0.05	(0.008)	0.07
Hours	0.20	(0.011)	0.20
Intermediate inputs	0.19	(0.035)	0.36
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.21
Labor productivity	0.02	(0.006)	0.04
Int. inputs per hour	0.07	(0.012)	0.40
True TFP	-	-	0.00
Post-1984 calibration			
Value added	0.11	(0.011)	0.07
Gross output	0.19	(0.011)	0.18
Measured TFP	0.06	(0.009)	0.04
Hours	0.25	(0.047)	0.12
Intermediate inputs	0.22	(0.020)	0.20
Output price	0.18	(0.037)	0.01
Input price	0.29	(0.055)	0.21
Labor productivity	0.07	(0.012)	0.04
Int. inputs per hour	0.09	(0.029)	0.24
True TFP	-	-	0.00

Table 5: Comparison of average cross-industry correlations in the model and in the data, growth rates of industry variables. Reported numbers are simple averages across pairwise industry correlations. Top panel: baseline calibration contrasted to the data in the pre-1984 period. Bottom panel: calibration with lower volatility of the aggregate demand shock compared to the post-1984 data. Bootstrapped standard errors.

co-moves more than in the data.

Of the many results reported in tables 3 - 5, we want to highlight several aspects. First, the correlations of all real aggregate variables with value added and with measured productivity are in line with the data. Moreover, the correlations of industry variables with industry value added and measured productivity are also matched well. Second, the model fits well the relative standard deviations of the variables. Noticeably, the model replicates the fact that gross output fluctuates more than value added at the aggregate level, but less than value added at the industry level. We further discuss this property in section 4.4. Third, the model does a good job in matching the average cross-industry correlations of most variables, although we do not target any of them. In particular, the average cross-industry correlations of measured productivity and of labor productivity are small, although significantly different from zero. In the next section we show that all technology shocks in the model are idiosyncratic industry-level shocks, and the positive correlation is generated by the aggregate demand shocks through endogenous effort and, to a smaller extent, due to increasing returns to scale.

4.2 What shocks are driving business cycle fluctuations?

Table 6 shows the variance decomposition of selected model variables. The most striking observation is that our model implies zero role for aggregate technology shocks. Technology shocks are present in the model, but all of them are industry-specific.

The top panel of table 6 displays the decomposition for the industry-level variables. Not

Variance Decomposition					
	Aggregate shocks		Industry shocks		Measurement
	technology	demand	technology	demand	error
Industry variables					
Value added	0.00	0.18	0.28	0.54	0.00
Gross output	0.00	0.35	0.05	0.60	0.00
Measured TFP	0.00	0.07	0.75	0.11	0.07
Hours	0.00	0.22	0.13	0.40	0.25
Intermediate inputs	0.00	0.42	0.14	0.44	0.00
Output price	0.00	0.05	0.94	0.01	0.00
Input price	0.00	0.05	0.94	0.01	0.00
Labor productivity	0.00	0.05	0.65	0.18	0.12
True TFP	0.00	0.00	1.00	0.00	0.00
Aggregate variables					
Value added	0.00	0.88	0.12	0.00	0.00
Gross output	0.00	0.95	0.04	0.01	0.00
Measured TFP	0.00	0.59	0.26	0.00	0.15
Hours	0.00	0.78	0.02	0.00	0.20
Intermediate inputs	0.00	0.96	0.02	0.02	0.00
Inflation	0.00	0.99	0.01	0.00	0.00
Labor productivity	0.00	0.20	0.35	0.00	0.45
Int. inputs per hour	0.00	0.81	0.03	0.05	0.12
Investment	0.00	0.92	0.08	0.00	0.00
Consumption	0.00	0.50	0.45	0.05	0.00
True TFP	0.00	0.01	0.99	0.00	0.00

Table 6: Variance decomposition of selected model variables, baseline calibration.

surprisingly, for all industry-level variables, the majority of the fluctuations is explained by the industry-specific shocks: industry demand shocks explain about a half of the fluctuations of industry-level value added and production inputs (capital, hours, intermediate inputs). On the other hand, shocks to technology are especially important for measured productivity and prices. Due to the high flexibility of factors across industries, industry relative prices react very little to an increased demand for the industry good.

The bottom panel of table 6 displays the variance decomposition for the aggregate variables. In this case, the effect of the industry-specific shocks is considerably smaller. The industry demand shocks do not contribute to aggregate fluctuations by construction, and industry shocks to technology wash out to a large extent. The majority of the fluctuations of the aggregate variables, including measured TFP, is explained by aggregate shocks to demand, due to endogenous effort and returns to scale, as we described in the previous sections. Fluctuations in hours are driven almost exclusively by demand shocks, but observed hours are by assumption also subject to sizeable measurement errors.

To the best of our knowledge, we are the first ones to attribute zero role to the aggregate technology shock in this class of models. Why do we come to different conclusions than the previous literature? In their seminal contribution, Foerster et al. (2011) estimate that idiosyncratic industry-specific shocks are responsible for 20% to 50% of the aggregate fluctuations in industrial production, depending on the sample period. The remaining fluctuations of aggregate variables in their model, as well as in multiple other contributions, are explained by an exogenous common factor that drives productivity, i.e., aggregate technology shock.

The reason why the existing literature assigned a big part of the fluctuations to the aggregate component of the technology shocks is that it is hard to generate the co-movement in measured productivity observed in the data from *independent* industry-level shocks only. Even though the average correlation of 0.05 in table 5 appears small, the aggregate component necessary to generate the co-movement turns out to be powerful enough to explain a major part of the aggregate fluctuations.[8] This is also true in our model. However, in our model the co-movement between measured productivity across industries can also arise from aggregate demand shocks.

Digging a bit deeper, we can describe how the individual mechanisms in our model alter the previous results. On the one hand, our model includes features that further reduce the role of industry technology shocks in comparison to the previous literature. First, the model includes industry demand shocks which explain a substantial part of the fluctuations at the industry level. Second, prices in the model are rigid, which suppresses the transmission of shocks across industries, cf. section 2.9. Both features imply that an even larger part of aggregate productivity fluctuations remains to be explained by aggregate shocks. However, in contrast to the literature, we do not assume that these aggregate shocks must be technology shocks. Table 3 shows that the standard deviation of growth in aggregate "true" technology, arising purely from technology shocks, is indeed less than half of the standard deviation of measured TFP. Put in another way, technology shocks in our model explain only about one fourth of the variance of aggregate measured TFP. As it turns out, industry technology shocks are sufficiently large to generate this part. The rest is generated by the changes in aggregate demand through endogenous factor utilization.

4.3 Moments within and across industries

Given the importance of the industry-level moments for the identification of shocks in our model, it is important to test whether the model generates a good fit across the individual industries. Therefore, we complement the industry-level averages reported in tables 4 and 5 with the information about the distribution of the moments across industries.

Industry-level second moments Figure 1 shows the distribution of the key industry-level moments across the 77 industries. Each plot compares the distribution in the data to the *population* distribution generated by the model under the baseline calibration. The population distribution depicts the industry moments averaged over a large number of simulations. The standard deviations of both distributions are reported in table 7.

All four moments display a large variation across industries, comparable between the data and the model. The model fits the distribution of the volatilities of measured TFP and gross

[8] To illustrate this point with a simple example, let us assume industries are symmetric, and aggregate (growth rate) variable X can be expressed using industry variables as $X = \sum_{i=1}^{I} \frac{1}{I} x_i$. Standard deviation of variable x_i in each industry is the same (equal σ) and pairwise correlation is the same for each pair of industries (equal c).

$$var(X) = \frac{1}{I^2}\sum_{i=1}^{I}\sum_{j=1}^{I} cov(x_i, x_j) = \frac{1}{I^2}\sum_{i=1}^{I} var(x_i) + \frac{1}{I^2}\sum_{i \neq j} corr(x_i, x_j) std(x_i) std(x_j) = \frac{1}{I}\sigma^2 + \frac{I-1}{I}\sigma^2 c$$

For $I = 77$ industries and the average correlation $c = 0.05$, the contribution of the off-diagonal elements to the aggregate variance is around 4 times bigger than that of the diagonal elements.

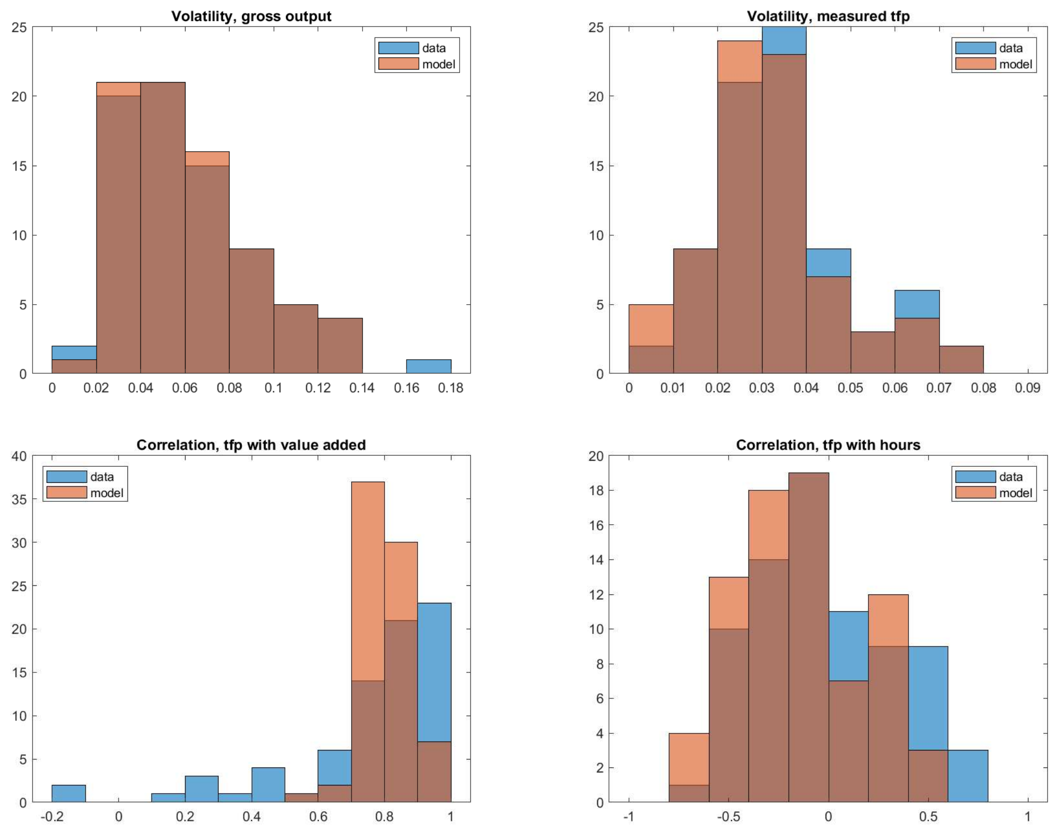

Figure 1: Distribution of industry-level second moments in the data and generated by the model. Baseline calibration. Top panel: volatility of gross output (left) and measured tfp (right). Bottom panel: correlation of measured tfp with output (left) and measured hours (right). The volatilities in the top panel are targeted in the SMM. The correlations in the bottom panel are results.

Distribution of within-industry and cross-industry correlations					
	Average correlation		Standard deviation (distribution)		
	Data	Model	Data	Model sampling	Model population
Within-industry correlations					
corr(va_i, $tfpm_i$)	0.76	0.80	0.24	0.11	0.07
corr(h_i, $tfpm_i$)	-0.03	-0.14	0.33	0.37	0.32
Cross-industry correlations					
Value added	0.14	0.13	0.29	0.25	0.15
Gross output	0.22	0.30	0.28	0.27	0.20
Measured TFP	0.05	0.07	0.27	0.22	0.07
Hours	0.20	0.20	0.29	0.23	0.12

Table 7: Distributions of within-industry and cross-industry correlations. Data, model population distribution, and (average) sample distributions. All averages are computed as simple means.

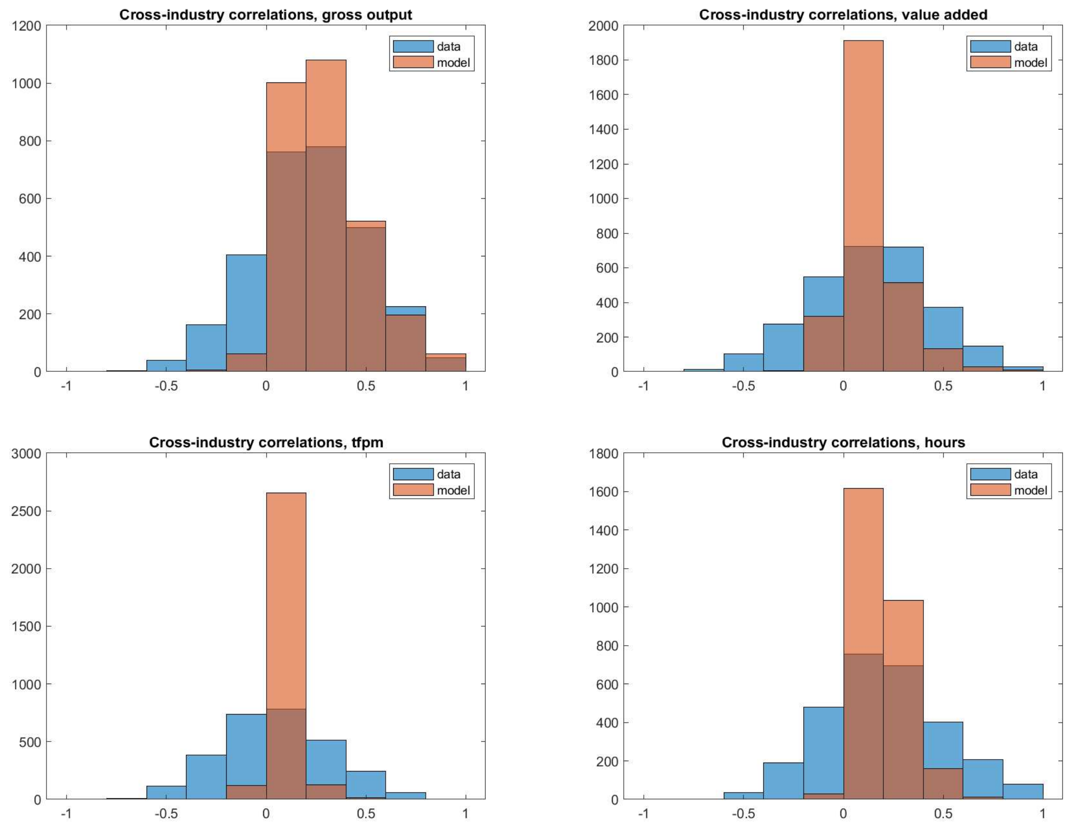

Figure 2: Histograms of pairwise cross-industry correlations of selected macroeconomic variables in the data and generated by the model. Baseline calibration, population distribution generated by the model.

output (top panels) almost perfectly, because the individual volatilities are targeted in the calibration procedure. For correlations of measured productivity with value added and hours (bottom panels of figure 1), the model generates a population distribution that is more concentrated compared to the data. In particular, the model completely misses a handful of industries with very low correlations between measured productivity and output. However, we have to consider that the data distribution contains sizeable sampling error, which is not reflected in the population distribution from the model.

To account for the sampling error, table 7 also reports the average standard deviation of the distributions generated in short model simulations, cf. column *model sampling*. Accounting for the sampling error brings the distribution of the model correlations closer to the data, although it can not generate the fat tail for the correlation between measured productivity and output.

Co-movement across industries We discussed the importance of the co-movement between industries for the aggregate fluctuations and displayed average cross-industry correlations in table 5. Figure 2 shows the distribution of the cross-industry correlations across the 2926 industry-pairs for four industry variables.

In all four cases, the correlations in the data are very dispersed. The bottom left panel plots the cross-industry correlations of measured total factor productivity, which range between -0.5

and 0.7. The average correlation is 0.05. The model generates a much more concentrated population distribution, which is also true for the other displayed variables. To account for sampling error, the bottom panel of table 7 again reports standard deviation for both long simulation (population distribution) and average across short model simulations (model sampling). While the heterogeneity in the population moments falls short of the data by a considerable margin, the typical distribution of a short model simulation displays a dispersion that is close to the one observed in the data.

In sum, the distributions generated by the model lend further credibility to our results. Despite a lot of symmetry imposed on the model industries, such as identical substitution elasticities and degree of price rigidity, the model generates a realistic level of industry-level heterogeneity.

4.4 Discussion of alternative modelling choices

The natural question is whether the results presented in sections 4.1 and 4.2 are robust, and how they compare with alternative model specifications. To make the main mechanisms driving the results more transparent, and to provide an intuition on which aspects of the data identify the model, we compare our baseline calibration against what we think are the two most relevant alternatives. First, endogenous effort explains most of the aggregate fluctuations in measured productivity, and thereby "crowds out" the aggregate technology shocks from our model. Thus, we re-calibrate a version of the model with constant effort and point out the dimensions in which this version does not fit the data. Second, we calibrate a version of the model with perfectly flexible prices, which is more comparable to the RBC-style industry-level models in the literature. For each alternative, we recalibrate the variances of all shocks. Detailed results for the two alternative versions of the model are available in appendix C.

Tables 9–12 present the results for the alternative model with constant effort. We recalibrate the variances of the shocks, while the remaining structural parameters are kept the same as in the baseline. In the absence of endogenous effort, our model assigns a substantial role to aggregate technology shocks, which explain 75 percent of the variance of aggregate measured TFP. However, aggregate technology shocks contribute very little to the fluctuations of aggregate hours, which are explained by demand shocks.

This version of the model calibration fails to match the data in several important ways. Most obviously, the model grossly overestimates the average cross-industry correlation of both measured TFP and of labor productivity. Aggregate technology shocks generate almost as much co-movement in measured productivity as in value added, at odds with the data: the cross-industry correlation of measured TFP increases to 0.13, compared to 0.05 in the data. Second, the model is not able to generate a positive correlation between aggregate hours and measured productivity. Both in New Keynesian models and empirically, technology shocks are associated with a small, and often negative, response of labor input, see the rich literature starting from Galí (1999). For similar reasons, the alternative calibration also fails to generate the strong positive correlation of intermediate inputs with measured productivity. Third, the volatility of aggregate gross output falls to about the same level as that of aggregate value added, while in the data it is substantially larger. We conclude that the empirical performance of the model deteriorates in several dimensions if we try to explain the movements in productivity by technology shocks rather than factor utilization.

The second alternative that we consider is the case of flexible prices. The baseline calibration follows the New Keynesian literature and assumes a price rigidity parameter θ_i equal to 0.75 in all industries. Variation of the parameter value within the range usually assumed in the literature does not substantially change our conclusions. However, with perfectly flexible prices (case $\theta_i = 0$) the model outcomes become independent of nominal variables. Therefore, the aggregate demand shock generates zero fluctuations. To give the model a better chance to fit the data, we eliminate additional rigidities in the model by setting the labor supply elasticity to infinity, decreasing the capital adjustment costs, and eliminating the consumption habit and the measurement error on hours. Tables 13–16 present the results for the model with flexible prices. Industry technology shocks explain a bigger part of the aggregate fluctuations, because their propagation across the input-output network is stronger. Again, aggregate technology shocks are important. The performance of the model worsens along the same dimensions in the case of constant effort, and by a wider margin. The cross-industry correlations of productivity measures are too high, basically the same as those of value added and gross output. On the other hand, the cross-industry co-movement of hours is too low. The correlation of aggregate measured productivity with hours is too high, as hours now follow a typical positive RBC response to technology shocks. Moreover, in this case the model is not able to generate a sufficiently high response of aggregate hours. Aggregate gross output fluctuates much less than GDP, contrary to the data. The relative prices at the industry level still fluctuate substantially less than in the data, but now their correlation with industry measured productivity is also too negative.

The discussion of the alternative models highlights the importance of the industry-level information. The version of the model with no aggregate technology shocks is strongly supported by the low cross-industry correlation of measured productivity compared to output and hours, and by the fact that aggregate gross output fluctuates more than value added. The importance of the relative variance of gross output for identification of demand versus technology shocks deserves some further explanation. Technology shocks tend to make aggregate value added react more strongly, in percentage terms, than gross output: if the elasticity of substitution between labor and intermediate inputs is lower than unity, and the labor input response to a technology shock is not too strong, then intermediate inputs change proportionally less than gross output. Therefore, value added reacts proportionally more than gross output. This is not the case for demand shocks, which generate a comparatively stronger reaction of production factors. This mechanism explains why at the industry level, where technology shocks are dominating, gross output fluctuates less than value added. On the contrary, at the aggregate level, where demand shocks are dominant, gross output fluctuates more. We provide a simple analytical analysis in appendix D.

A further industry-level statistic that speaks in favor of endogenous effort is the ratio of intermediate inputs per hour worked. The ratio is fluctuating in all three model variants because the relative price of labor and intermediate inputs is changing in response to the shocks. However, there is a further mechanism in the case of endogenous effort: cost minimization determines the ratio of intermediate inputs to *effective* labor input, given factor prices. With flexible effort, effective labor input fluctuates more than hours, making intermediate inputs per hour more volatile. This explains why the ratio of intermediate inputs per hour worked in the baseline model fluctuates more than in the two alternatives. Comparing tables 4, 10 and 14 shows that the average standard deviations of the ratio of intermediate inputs per hour at the industry level is 0.73 in the data, 0.52 in the baseline model, 0.30 in the model with constant effort, and 0.25 in the model with flexible prices, supporting the baseline calibration.

4.5 Changes in business cycle co-movement after 1984

Finally, we analyse the alternative calibration that tests the predictions of the model for the great moderation period. A growing branch of literature tries to explain the changes in the business cycle fluctuations in the U.S. in the mid-1980s, in particular the vanishing cyclicality of productivity. Molnárová (2020) shows that industry evidence provides important information for assessing the plausibility of the proposed explanations. A number of the mechanisms proposed in the literature imply that the changes in cyclicality should be equally visible at the industry and the aggregate level. This is not the case in the data. In this section, we investigate to what extent our model is able to explain the changes in the mid-1980s taking into account both aggregate and industry-level evidence.

The bottom panels of tables 3 - 5 show the data moments in the post-1984 period and simulation results for the alternative calibration. The comparison of the industry data moments (tables 4 - 5) for periods before and after 1984 shows that many of the business cycle statistics are remarkably stable between the two sub-samples. While the absolute size of the fluctuations is smaller in the post-1984 period, most of the relative volatilities and correlations do not change much. However, the comparison of the aggregate data moments between the periods pre- and post-1984 in table 3 shows that there are some important differences.

- The absolute size of the aggregate fluctuations is smaller in the post-1984 period.
- The correlation between aggregate measured productivity and hours decreased from 0.49 to -0.26, the correlation with output decreased from 0.85 to 0.47, the change for measured labor productivity being similarly striking. Other correlations reported in the table also decreased in the post 1984-period, although the differences are much smaller.
- Standard deviations of aggregate factor inputs, labor and intermediate inputs, increased relative to the standard deviation of value added.
- The ratio of intermediate inputs over hours, at the aggregate level became less correlated with output and productivity.

Several authors have suggested that the great moderation period after 1984 was characterised by a different composition of shocks, especially stressing the lower volatility of shocks to aggregate demand, or muted effects of these shocks on the economy, see e.g. Barnichon (2010) and Galí and Gambetti (2009). Therefore, we decrease the volatility of the aggregate demand shock in our model in line with the empirical evidence and test the model predictions for the cyclicality of measured productivity. We keep the rest of the parameters, including the variances of industry shocks, the same as in the baseline. We decrease the volatility of the aggregate demand shock σ_D by around 40% such that the model exactly replicates the moderate decrease in the correlation of output and measured hours observed in the data.

The bottom panels of tables 3 and 4 show the second moments of the model variables generated using this alternative calibration and compare them to the data in the post-1984 period. The single change in the calibration of our model generates a significant part of the vanishing cyclicality of labor productivity observed in the aggregate data. In the model, the correlation between aggregate measured TFP and hours decreases to 0.11, which corresponds to 50% of the observed change. The correlation between measured TFP and output decreases from 0.87 to 0.79, which corresponds to 19% of the observed change. At the same time, the correlation between measured TFP and value added at the industry level stayed on average virtually unchanged both in the data and in the model. The average correlation between the industry measured TFP and hours in the data decreased moderately from -0.02 to -0.23, while the model generates around 65% of the decrease, from -0.06 to -0.20.

To summarize, the alternative calibration of the model replicates the post-1984 decrease in the volatility of aggregate output and productivity, and it generates a significant part of the decrease in the procyclicality of measured aggregate productivity, without generating a counterfactual decrease in procyclicality of productivity at the industry level. Looking at a larger set of moments, however, there are several dimensions along which the alternative calibration is less successful. In particular, the correlation of aggregate measured productivity with output and intermediate inputs has decreased significantly more in the data than in the model.

5 Concluding remarks

In this paper, we have developed a highly disaggregated DSGE model with input-output linkages between industries. We use this framework to study the relative importance of technology and demand shocks, both at the aggregate and industry level. Our model supports the view that there are no aggregate technology shocks. We find that all the variation in observed productivity can be explained by two components: idiosyncratic technology shocks at the industry level and endogenous variations in factor utilization, driven by shocks to aggregate demand. Considering only aggregate empirical evidence, it would be difficult to distinguish between a model with endogenous effort and a model with aggregate technology shocks. However, we show that the model with endogenous effort matches the industry-level evidence much better than the model with aggregate technology shocks. There is small but highly important co-movement of measured productivity across industries, which points towards the presence of an aggregate component. The co-movement pattern is explained well in our model with endogenous fluctuations in effort, caused by the aggregate shocks to demand, while it is exaggerated in the model with aggregate technology shocks.

Our results support a Keynesian view of business cycles in the sense that aggregate demand shocks are the main driver of aggregate fluctuations. They explain 78 percent of the fluctuations in aggregate hours, with the remaining part being attributed to measurement errors. This is in line with recent evidence in Angeletos et al. (2020) and Andrle et al. (2017). Since we model the aggregate demand shock as a risk premium wedge affecting the inter-temporal substitution, we also see our results as consistent with Hall (2017), who shows that fluctuations in employment are primarily driven by changes in financial discount factors. Our estimates attach an important role to endogenous effort, in line with Fernald and Wang (2016), who find that the procyclicality of measured productivity is mostly due to endogenous factor utilization.

We have also explored to what extent our model can account for the change in the cyclicality of productivity after the mid-1980s. We find that a reduction in the variance of aggregate demand shocks, compatible with the great moderation narrative, explains a substantial part of the reduction in correlations between aggregate measured productivity and labor input. However, it explains only a small part of the change of some other moments, such as correlation between aggregate productivity and output. Clearly, there are other aspects of the changes in the great moderation period which our model does not take into account. While we cannot fully account for the change in the cyclical properties of productivity after 1984, our results support the view that the vanishing cyclicality of measured productivity should not be interpreted as a reduced role of technology shocks. In fact, technology shocks have never been a major driver in the procyclicality of measured productivity in the first place.

Our findings have potential implications for both monetary and fiscal policy. For monetary policy, the correct identification of productivity shocks is crucial for determining the output gap. Kiley (2013) shows that the estimated output gap in DSGE models is strongly affected by the estimated variations in measured aggregate technology. Thus, the correct identification of sources of the macroeconomic fluctuations, both real-time and ex post, is important for choosing the adequate reaction of monetary policy. Moreover, the response of monetary policy following an industry-specific shock might have stronger redistributive effects.

The recent literature has stressed the stabilization role of fiscal policy after shifts in aggregate demand. Government purchases of goods and services generate demand in the specific industries which spill over to the rest of the economy. Due to differences in the industry structure and input-output network, the effects of fiscal policies depend on the allocation of resources across industries. Understanding the transmission mechanisms in a disaggregated general equilibrium model can help identify those fiscal measures that are most effective in generating output and employment. Koch and Molnárová (2020) explore the issue in the context of small open economy.

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A First order conditions and equilibrium

A.1 Optimal composition of labor input

For any given firm demand for labor input $\bar{l}$, households are free to choose how much effort e and hours h they supply such that $\bar{l} = eh$. In each period, the optimizing household chooses hours and effort supplied to industry i to minimize the disutility from working

$$\min_{h_i, e_i} g(h_i, e_i), \tag{37}$$

such that

$$h_i e_i = \bar{l}_i, \tag{38}$$

where function g is given in 10. The associated first order condition gives

$$e_i = \Lambda_i^{-\frac{1}{\sigma_e}} h_i^{\frac{\sigma_h}{\sigma_e}}. \tag{39}$$

Substituting into equation 11 we get

$$h_i = \Lambda_i^{\frac{1}{\sigma_e + \sigma_h}} l_i^{\frac{\sigma_e}{\sigma_e + \sigma_h}} \tag{40}$$

Substituting 39 into 10 we get

$$\begin{aligned} g(e_i, h_i) &= \kappa_0 h_i^{\frac{\sigma_e + \sigma_h}{\sigma_e}} && (41) \\ &= \kappa_0 \Lambda_i^{\frac{1}{\sigma_e}} l_i, && (42) \end{aligned}$$

where

$$\kappa_0 = \left(\frac{\sigma_e + \sigma_h}{\sigma_e \sigma_h} \right)^{\frac{\sigma_h + \sigma_e}{\sigma_h \sigma_e}}. \tag{43}$$

Function g is linear in effective labor input l_i, which implies that the household problem is convex (budget constraint is linear in l_i and household utility function is convex in g).

A.2 Household problem

Households maximize their objective function 4 with respect to the budget constraint 13, capital evolution equation 22, non-negativity constraints on K_t, $l_{i,t}$ and C_t and two no-Ponzi conditions corresponding to the two assets B_t, K_t. In a symmetric equilibrium, no household can borrow in bonds or hold negative capital. Thus, the no-Ponzi conditions are always satisfied. The problem of the household is convex and leads to an interior solution, thus the non-negativity constraints are always satisfied. We solve the reduced problem of maximizing 4 with respect to

13 and 22 by differentiating the Lagrangian:

$$\begin{aligned}
C_t &: \lambda_t = U_C(C_t, N_t) && (44)\\
l_{i,t} &: -\lambda_t w_{i,t} = U_{l_i}(C_t, N_t) && (45)\\
B_t &: \lambda_t = \beta\,\mathrm{E}_t\left[\lambda_{t+1} r^B_{t+1}\right] && (46)\\
K_t &: \nu_t = \beta\,\mathrm{E}_t\left[\nu_{t+1}(1-\delta+\phi(\iota_{t+1})) + \beta\lambda_{t+1}(r^k_{t+1} - P^X_{t+1}\iota_{t+1})\right] && (47)\\
\iota_t &: \lambda_t P^X_t = \nu_t \phi_\iota(\iota_t) && (48)
\end{aligned}$$

where λ_t and ν_t are Lagrange multipliers corresponding to constraints (13) and (22), respectively. U_C and U_{l_i} denote the derivatives of household objective function w.r.t. the corresponding variables.

Equations 44 and 45 together lead to the intratemporal condition

$$-w_{i,t}U_C(C_t, N_t) = U_{l_i}(C_t, N_t). \tag{49}$$

Equations 44 and 46 together yield the household Euler equation

$$U_C(C_t, N_t) = \beta\,\mathrm{E}_t\, D_t \frac{R_t}{\pi_{t+1}} U_C(C_{t+1}, N_{t+1}). \tag{50}$$

Using the standard definition of Tobin's Q (denoted Q^T), equation 48 can be rearranged as

$$\nu_t = P^X_t \frac{\lambda_t}{\phi_\iota(\iota_t)} = P^X_t \lambda_t Q^T_t \tag{51}$$

and plugged into equation 47 to obtain the optimal investment condition

$$Q^T_t = \mathrm{E}_t\, Q_{t,t+1}\pi^X_{t+1}\left[\frac{r^k_{t+1}}{P^X_{t+1}} - \iota_{t+1} + Q^T_{t+1}(1-\delta+\phi(\iota_{t+1}))\right], \tag{52}$$

where

$$\pi^X_{t+1} = \frac{P^X_{t+1}}{P^X_t}\frac{P_{t+1}}{P_t} = \frac{P^X_{t+1}}{P^X_t}\pi_{t+1} \tag{53}$$

is the inflation in the nominal price of capital.

A.3 Firm problem

Given the firm prices, the demand for products of each firm is determined. Firm k in industry i faces the problem of optimal choice of production inputs, such that it can satisfy the demand.

$$\min_{k_{ki,t}, l_{ki,t}, m_{k,1..I,t}} w_{i,t} l_{ki,t} + r^k_t k_{ki,t} + \sum_j p_{j,t} m_{k,ji,t} \tag{54}$$

such that

$$y_{ki,t}(p_{ki,t}) + \Phi_i = F^i(A_t, z_{i,t}, k_{ki,t}, l_{ki,t}, M_{ki,t}), \tag{55}$$

where F^i is the production function in industry i, $l_{ki,t}$, $k_{ki,t}$, $M_{ki,t}$ are firm-level input factors and $w_{i,t}$, $r^k_{i,t}$, $P^M_{i,t}$ are the corresponding prices.

Optimal behaviour of firms in industry i implies that the first order condition

$$\frac{m_{j_1,i}}{m_{j_2,i}} = \frac{\alpha_{j_1,i}}{\alpha_{j_2,i}} \left(\frac{p_{j_2}}{p_{j_1}}\right)^{\sigma_M} \tag{56}$$

holds for each j_1, j_2. The price index of intermediate goods used in industry i, $P^M_{i,t}$, follows from the production function of intermediate good M_i,

$$P^M_{i,t} = \left(\sum_{j=1}^{I} \alpha_{ji} {p_{j,t}}^{1-\sigma_M}\right)^{\frac{1}{1-\sigma_M}}. \tag{57}$$

Due to the constant returns to scale technology for M_i, the price index is the same for all firms in industry i, as they optimally choose the same composition of intermediate inputs.

Differentiating the Lagrangian w.r.t. $l_{ki,t}$, $k_{ki,t}$, $M_{ki,t}$ we obtain the standard conditions

$$\frac{w_{i,t}}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial l_{ki,t}} \tag{58}$$

$$\frac{r^k_t}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial k_{ki,t}} \tag{59}$$

$$\frac{P^M_{i,t}}{\lambda_{ki,t}} = \frac{\partial F^i}{\partial M_{ki,t}} \tag{60}$$

where $\lambda_{ki,t}$ is the Lagrange multiplier associated with condition 55. The first two conditions lead to

$$\frac{w_{i,t}}{r^k_t} = \frac{\partial F^i / \partial l_{ki,t}}{\partial F^i / \partial k_{ki,t}} \tag{61}$$

and the second two conditions give

$$\frac{w_{i,t}}{P^M_{i,t}} = \frac{\partial F^i / \partial l_{ki,t}}{\partial F^i / \partial M_{ki,t}}. \tag{62}$$

It is straightforward to derive the firm-level optimality condition

$$RMC_{i,t} = \frac{r^k_t}{\partial F^i / \partial k_{ki,t}}, \tag{63}$$

and analogous conditions for $l_{ki,t}, M_{ki,t}$, where real marginal costs are given as

$$RMC_{i,t} = \frac{1}{A_t z_{i,t}} \left(\mu_{i,K} {r^k_t}^{1-\sigma_y} + \mu_{i,L} {w_{i,t}}^{1-\sigma_y} + \mu_{i,M} {P^M_{i,t}}^{1-\sigma_y}\right)^{\frac{1}{1-\sigma_y}}. \tag{64}$$

Equation 63 implies that all firms operating in industry i choose inputs such that the partial derivatives $\partial F^i / \partial k_{ki,t}$ are the same across firms. Equations 61 to 63 thus hold at the industry level as well.

Apart from the fixed costs, the production technology is constant returns to scale, therefore real costs are linear in output.

$$Costs(y_{ki,t} + \Phi_i) = RMC_{i,t} \cdot (y_{ki,t} + \Phi_i). \tag{65}$$

Plugging the production function 15 into 63 and reorganizing, we get

$$k_{ki,t} = (A_t z_{it})^{\sigma_y - 1} \mu_{i,K} \left(\frac{r^k_{i,t}}{RMC_{i,t}} \right)^{-\sigma_y} (y_{ki,t} + \Phi_i)., \tag{66}$$

and corresponding equations for labor and intermediate inputs.

A.4 Industry production

Industry demand for labor follows from the market clearing condition

$$\begin{aligned} l_{i,t} &= \int_0^1 l_{ki,t}\, dk \quad (67) \\ &= \Theta_{i,t} \int_0^1 y_{ki,t} + \Phi_i\, dk \quad (68) \\ &= \Theta_{i,t}\Phi_i + \Theta_{i,t} y_{i,t} \int_0^1 \left(\frac{p_{ki,t}}{p_{i,t}} \right)^{-\sigma_I} dk, \quad (69) \end{aligned}$$

where

$$\Theta_{i,t} = (A_t z_{it})^{\sigma_y - 1} \mu_{i,L} \left(\frac{w_{i,t}}{RMC_{i,t}} \right)^{-\sigma_y} \tag{70}$$

depends on industry-level prices and parameters only. Expression

$$Disp_{i,t} = \int_0^1 \left(\frac{p_{ki,t}}{p_{i,t}} \right)^{-\sigma_I} dk \tag{71}$$

is the price dispersion term. A standard result from the New Keynesian literature shows that the dispersion term has only second-order effects around the zero-inflation steady state. It follows that

$$l_{i,t} \approxeq (A_t z_{i,t})^{\sigma_y - 1} \mu_{i,L} \left(\frac{w_{i,t}}{RMC_{i,t}} \right)^{-\sigma_y} (y_{i,t} + \Phi_i), \tag{72}$$

up to the first order approximation.

Next, we derive the total demand for a particular good i and show it is independent of firm-specific variables up to the first order approximation. We start with determining the demand for i as intermediate input. In line with 72, demand for intermediate good aggregate $M_{j,t}$ in industry j is

$$M_{j,t} \approxeq (A_t z_{j,t})^{\sigma_y - 1} \mu_{j,M} \left(\frac{P^M_{j,t}}{RMC_{j,t}} \right)^{-\sigma_y} (y_{j,t} + \Phi_j). \tag{73}$$

An optimizing firm k in sector j chooses intermediate input from sector i according to

$$m_{k,ij,t} = \alpha_{ij} \left(\frac{p_{i,t}}{P^M_{j,t}} \right)^{-\sigma_M} M_{kj,t} \tag{74}$$

Total intermediate input i as an input into industry j production can be expressed as

$$\begin{aligned} m_{ij,t} &= \int_0^1 m_{k,ij,t}\, dk && (75)\\ &= \alpha_{ij}\left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M}\int_0^1 M_{kj,t}\, dk && (76)\\ &\approxeq \Gamma_{ij,t}(y_{j,t}+\Phi_j), && (77)\end{aligned}$$

where the parameter $\Gamma_{ij,t}$ is independent of the firm's actions,

$$\Gamma_{ij,t} = \alpha_{ij}\mu_{j,M}(A_t z_{j,t})^{\sigma_y - 1}\left(\frac{p_{i,t}}{P^M_{j,t}}\right)^{-\sigma_M}\left(\frac{P^M_{j,t}}{RMC_{j,t}}\right)^{-\sigma_y}. \tag{78}$$

Thus, the total demand for industry i's good can be expressed as

$$\begin{aligned} y_{i,t} &= c_{i,t} + x_{i,t} + \sum_j m_{ij,t} && (79)\\ &\approxeq v_{i,t}{p_{i,t}}^{-\sigma_C} C_t + \xi_i\left(\frac{p_{i,t}}{P^X_t}\right)^{-\sigma_X} X_t + \sum_j \Gamma_{ij,t}(y_{j,t}+\Phi_j). && (80)\end{aligned}$$

A.5 Price setting

The period $t+s$ demand for the product of a firm that has last updated its price in period t can be expressed using 2 as

$$y_{ki,t+s|t} = \left(\frac{p^{NOM}_{ki,t}}{p^{NOM}_{i,t+s}}\right)^{-\sigma_I} y_{i,t+s} \tag{81}$$

where superscript NOM denotes the nominal prices. Equation 80 shows that $y_{i,t+s}$ does not depend on the individual firm-level variables.
In nominal terms, the price-setting problem of each firm is to maximize 17:

$$\max_{p_{ki,t}, y_{ki,t}, \cdots, y_{ki,\infty}} \mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s}\left[y_{ki,t+s|t}(p^{NOM}_{ki,t} - NMC_{i,t+s}) - \Phi_i NMC_{i,t+s}\right]. \tag{82}$$

with respect to 81. Nominal marginal costs NMC are defined as

$$NMC_{i,t} = P_t \cdot RMC_{i,t} \tag{83}$$

Differentiating the Lagrangian we obtain

$$\begin{aligned} p^N_{ki,t} &: \mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s} y_{ki,t+s|t} - \sum_{s=0}^{\infty} \varrho_{t+s}\sigma_I \frac{(p^{NOM}_{ki,t})^{-\sigma_I - 1}}{(p^N_{i,t+s})^{-\sigma_I}} y_{i,t+s} = 0 && (84)\\ y_{ki,t+s|t} &: {\theta_i}^s Q_{t,t+s}[p^{NOM}_{ki,t} - NMC_{i,t+s}] = -\varrho_{t+s} && (85)\end{aligned}$$

ϱ_t denoting the Lagrange multiplier corresponding to the constraint 81 at time t. Substituting

85 into 84 we get

$$\mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s} \left[y_{ki,t+s|t} - [p_{ki,t}^{NOM} - NMC_{i,t+s}] \sigma_I \frac{(p_{ki,t}^{N})^{-\sigma_I - 1}}{(p_{i,t+s}^{N})^{-\sigma_I}} y_{i,t+s} \right] = 0 \tag{86}$$

$$\mathrm{E}_t \sum_{s=0}^{\infty} {\theta_i}^s Q_{t,t+s} y_{ki,t+s|t} \left[p_{ki,t}^{NOM} - \frac{\sigma_I}{\sigma_I - 1} NMC_{i,t+s} \right] = 0 \tag{87}$$

In a symmetric equilibrium, all firms within an industry i that set their prices in period t choose the same optimal price $p_{ki,t}^{NOM} = p_{i,t}^{NOM*}$.

A.6 Aggregation

$$H_t = \sum_{i=1}^{I} h_{i,t} \tag{88}$$

$$H_t^m = \sum_{i=1}^{I} h_{i,t}^m \tag{89}$$

$$K_{t-1} = \sum_{i=1}^{I} k_{i,t} \tag{90}$$

$$P_t^Y Y_t = \sum_{i=1}^{I} p_{i,t} y_{i,t} \tag{91}$$

$$P_t^{\dot{M}} \dot{M}_t = \sum_{i=1}^{I} P_{i,t}^M M_{i,t} \tag{92}$$

A.7 Equilibrium

The equilibrium of the generalized model is determined by the following set of $14 + 15 \times I$ equations:

- $2 + 2I$ exogenous shock processes 25 - 29
- $2 + 2I$ FOCs from household problem 39, 49, 50, 52
- $3I$ FOCs from firm cost-optimisation 61 - 63
- I firm production functions 15
- I FOCs from firm price setting problem 87
- I industry price evolution equations 16
- I optimal demand for industry good in final consumption conditions 7
- I optimal demand for industry good in investment creation 19
- I equations for price indexes of industry intermediate inputs 57
- I equations for effective labor input 11
- I good market clearing conditions 24
- 1 Taylor rule 23
- 1 capital evolution equation 22

- 1 equation defining aggregate investment 21
- 1 relative price of investment good 20
- 1 CPI normalization
- 5 aggregating equations for Y, K, H^m, H, $\dot{M}$ 88 - 92

The equations jointly solve for the following $14 + 15 \times I$ variables:

- $2 + 2I$ exogenous shocks A, D, z_i, v_i
- 12 aggregate variables Y, K, H^m, H, M, X, C, r, r^k, ι, π, P^X
- $13I$ industry variables y, k, l, h, M, p, P^M, c, e, x, w, RMC, p^*

Moreover, in the numerical solution and in the analysis of model results we use the following auxiliary variables:

- 10 aggregate variables VA, π^X, λ, Q, Q^T, T, II/H, LP, $TFPm$, TFP
- $8I$ industry variables va, $prof$, wh, ii/h, lp, tfp, SA, SB

Each of the auxiliary variables is defined by a corresponding equation. In total, our numerical programme features $24 + 23 \times I = 1795$ variables.

B Data and calibration

B.1 Additional information about the data

The primary data source that we use is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and 2005, disaggregated into 88 industries. This appendix describes in detail the construction of data series, aggregates, and data moments.

In line with the literature, we focus on the private business sector which consists of 77 industries. We aggregate the industry-level series of the private business sector to obtain the aggregate series. We exclude all government industries and the *Private households* industry. Government industries are usually omitted from productivity exercises because market prices are not available for government industries and are set arbitrarily. In my data, an additional problem with the government industries is that the information about intermediate inputs is often missing. In one case, a private industry (*59 Real estate - owner occupied dwellings*) does not utilize all inputs, as the only input is capital.

Table 8 lists the private sector industries and their relative shares in nominal output.

	List of industries, private business sector, part 1		
		gross output nominal share	value added nominal share
1	Farms	2.48	2.43
2	Agricultural services, forestry	0.37	0.35
3	Fishing	0.12	0.12
4	Metal mining	0.12	0.14
5	Nonmetal mining	0.15	0.21
6	Coal mining	0.26	0.39
7	Oil and gas extraction	1.52	1.90
8	Construction	7.04	6.65
9	Lumber and wood	0.89	0.69
10	Furniture and fixtures	0.53	0.49
11	Nonmetallic mineral products	0.76	0.83
12	Primary metals	1.68	1.39
13	Fabricated metal production	1.91	1.94
14	Machinery excl. computers	2.17	2.33
15	Computers and office equipment	0.76	0.45
16	Insulated wire	0.21	0.23
17	Audio and video equipment	0.12	0.09
18	Other electrical machinery	0.73	0.78
19	Communications equipment	0.46	0.45
20	Electronic components	0.78	0.61
21	Motor vehicles	2.64	1.22
22	Aerospace	1.13	1.22
23	Ships and boats	0.17	0.22
24	Other transportation equipment	0.17	0.15
25	Measuring instruments	0.62	0.67
26	Medical equipment and opthalmic goods	0.39	0.32
27	Other instruments	0.21	0.28
28	Misc. manufacturing	0.41	0.43
29	Food	3.99	2.33
30	Tobacco	0.23	0.19
31	Textile	0.70	0.63
32	Apparel	0.65	0.73
33	Leather	0.11	0.16
34	Paper and allied	1.28	1.05
35	Publishing	0.88	0.98
36	Printing and reproduction	0.68	0.72
37	Chemicals excl. drugs	2.39	1.98
38	Drugs	0.65	0.54
39	Petroleum and coal products	1.83	0.54
40	Rubber and misc. plastics	1.10	0.86

List of industries, private business sector, part 2			
		gross output nominal share	value added nominal share
41	Railroad transportation	0.43	0.75
42	Local passenger transit	0.22	0.40
43	Trucking and warehousing	1.75	1.83
44	Water transportation	0.34	0.34
45	Air transportation	0.83	0.67
46	Transportation services and pipelines	0.31	0.30
47	Telephone and telegraph	2.04	2.14
48	Radio and TV	0.53	0.39
49	Electric utilities (pvt)	2.05	2.28
50	Gas utilities	0.68	0.38
51	Water and sanitation	0.18	0.12
52	Wholesale trade	5.46	6.64
53	Retail trade excl. motor vehicles	4.40	5.78
54	Retail trade, motor vehicles	1.20	1.45
55	Eating and drinking	2.06	1.79
56	Depository institutions	2.74	2.40
57	Nondeposit; Sec-com brokers; Investment	1.76	1.51
58	Insurance carriers, agents, services	2.23	1.89
59	Real Estate - owner occupied	2.71	5.11
60	Real Estate - other	5.63	7.79
61	Hotels	0.77	0.88
62	Personal services	0.72	0.73
63	Business services excl. computer	2.48	2.70
64	Computer services	1.27	0.89
65	Auto services	1.01	0.86
66	Misc. repair services	0.42	0.58
67	Motion pictures	0.40	0.29
68	Recreation services	0.80	0.70
69	Offices of health practitioners	2.12	2.20
70	Nursing and personal care facilities	0.46	0.43
71	Hospitals, private	2.00	1.87
72	Health services, nec	0.53	0.47
73	Legal services	1.06	1.12
74	Educational services (private)	0.81	0.78
75	Social services and membership org.	1.49	1.34
76	Research	0.42	0.37
77	Misc professional services	2.38	2.11

Table 8: List of private industries, Jorgenson and coauthors. Percentage shares of industry nominal gross output and value added in total gross output and value added, average for 1960-2005.

B.1.1 Gross output

Jorgenson database reports industry nominal gross output and producers price indexes normalized in 1996. Therefore, I express real gross output (and other real variables) in 1996 dollars. Aggregate real gross output is defined as the sum of real outputs across the 77 industries of the private business sector.

B.1.2 Intermediate inputs

Real volumes of intermediate inputs can be expressed in 1996 dollars using the reported purchasers price index. I use Fisher price index in order to aggregate the real intermediate inputs delivered to a particular industry. This approach is consistent with the model economy, where the variety of intermediate inputs $m_{j,i,t}$ is aggregated into input $M_{i,t}$ according to a CES function.

Notice that gross output and intermediate input goods are not counted in consistent real units, as the two price indexes differ. Moreover, intermediate inputs reported in the database include imports, but the information about exports is not available. For these reasons, the goods market clearing identity at the industry level does not hold.

$$\text{gross output} \neq \text{consumption} + \text{investment} + \text{intermediate inputs}$$

The discrepancy is important for several reasons. First, value added can not be computed as a simple difference between gross output and intermediate inputs. Second, as we will see later, the measures of productivity are not comparable across industries.

B.1.3 Labor input

The measure of labor input reported in the Jorgenson data set is effective hours. Effective hours are defined as total hours adjusted for the composition of workforce, taking into account basic observable characteristics (education, age and gender).

The Jorgenson database reports nominal costs of effective labor and a price index for each industry, which allow to compute the real labor input series. However, the units are not comparable across industries. For the sake of easier interpretation, I rescale the real labor input series to approximately reflect effective hours worked in each industry. I use the 72-industry version of EU KLEMS data (based on SIC classification of industries) as an additional data source in order to pin down the effective hours and hourly wages in each industry in 1996. I apply these wages to the labor costs information in the Jorgenson data set in order to express the real labor input in hours. The rescaling of labor input series does not affect the results, but has the advantage that it allows me to define aggregate hours as a sum of industry hours.

Although the two data sets are based on the same accounting principles, there are several issues with matching the EU KLEMS to Jorgenson KLEMS. I resolve these issues using ad-hoc rules which try to minimize the effect of the discrepancies.

- The level of disaggregation in some cases differs between the two datasets. In case several Jorgenson industries constitute a single EU KLEMS industry, I used the same wage level for all the industries. In one case a Jorgenson industry (*63 Business services excluding computer services*) corresponds to two EU KLEMS industries. I approximated the wage in this industry by a weighted average of wages in both the EU KLEMS industries. Some EU KLEMS service industries include both private and government sector, while I only focus on the private sector in the Jorgenson data. It is likely that the wages in the private and government sector differ, however, a large discrepancy is rather unlikely. In this case, I consider the wages reported in the EU KLEMS data set to apply for the private-sector industries in the Jorgenson data. In one case (*51 Water and sanitation*) the labor compensation and hours data in the EU KLEMS are missing. I use the wage information from the *50 Gas utilities* industry, which I consider to be the closest approximation.

- I chose 1996 as the base year for pinning down the industry-level wages in the EU KLEMS data. The results are robust with respect to the choice of base year.

B.1.4 Capital accounts

Measuring the capital stock and capital services is typically the most challenging part of the growth accounting. Jorgenson database provides the nominal values and price index for the capital services in each industry. The KLEMS growth accounting is based on the assumption of perfect competition and zero profits. However, the nominal value of capital services is identified as the residual between value added and labor compensation. Therefore, it includes both the user cost of capital and profits.

The model abstracts from endogenous capital and assigns the non-labor income exclusively to firm profits. Since labor productivity is potentially affected by the fluctuations in capital services, it is more suitable to compare the model outcomes with measured total factor productivity.

B.1.5 Value added

Because the data set does not allow to compute outputs and intermediate inputs in consistent real units, I can not compute industry real value added as a simple difference between the two series. I thus follow the standard growth accounting methodology and define real value added using the so-called double deflation method (Timmer et al. 2007). The method provides growth rates series of value added for each industry. Nevertheless, it does not provide level series in units that are consistent across industries. I define aggregate real value added as aggregate nominal value added divided by the Fisher price index associated with the industry-level prices.

B.2 Bottom-up construction of aggregate series

B.2.1 Approximation formulas

Let us assume that the aggregate variable X_t can be expressed (exactly) as

$$X_t = \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t}, \tag{93}$$

where x_{it} are the industry level series and $\hat{w}_{it}$ are time varying weights. Then, for the growth rate of the aggregate variable it follows that

$$\begin{aligned}
\tilde{X}_{t+1} &= \frac{X_{t+1} - X_t}{X_t} \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t+1}x_{i,t+1} - \sum_{i=1}^{N} \hat{w}_{i,t}x_{i,t}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t+1}x_{i,t+1} - \sum_{i=1}^{N} \hat{w}_{i,t}x_{i,t+1} + \sum_{i=1}^{N} \hat{w}_{i,t}x_{i,t+1} - \sum_{i=1}^{N} \hat{w}_{i,t}x_{i,t}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t}(x_{i,t+1} - x_{i,t}) + \sum_{i=1}^{N} (\hat{w}_{i,t+1} - \hat{w}_{i,t})x_{i,t+1}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t}x_{i,t}\tilde{x}_{i,t+1} + \sum_{i=1}^{N} \tilde{w}_{i,t+1}\hat{w}_{i,t}x_{i,t+1}\right) \\
&= \sum_{i=1}^{N} w_{i,t+1}\tilde{x}_{i,t+1} + \sum_{i=1}^{N} \tilde{w}_{i,t+1}\frac{\hat{w}_{i,t}x_{i,t+1}}{X_t},
\end{aligned}$$

where $\tilde{x}_{i,t}$ is the growth rate between periods t and $t-1$ of industry-level variable x_i, $\tilde{w}_{i,t+1}$ is the growth rate of weight $\hat{w}_i$ and where in the last equation we have defined

$$w_{i,t+1} = \frac{\hat{w}_{i,t}x_{i,t}}{X_t}.$$

Notice that if the growth rate of weights $\tilde{w}_{i,t+1}$ is small, the second term is negligible and we obtain expression

$$\tilde{X}_t \approx \sum_{i=1}^{N} w_{i,t}\tilde{x}_{i,t}. \tag{94}$$

B.2.2 Weights

For gross output, value added, capital, hours and industry-level total intermediate inputs, the aggregate nominal value is the sum of industry nominal values. Thus, I can substitute into equation 93 directly with

$$X_t^{real} = \sum_{i=1}^{N} \frac{p_{i,t}^x}{P_t^X} x_{i,t}^{real}, \tag{95}$$

where x_i is the industry variable of interest, $p_{i,t}^x$ is the price of $x_{i,t}$ and P_t^X is the corresponding price index. It follows that I can substitute into 93 and 94

$$\hat{w}_{it} = \frac{p_{i,t}^x}{P_t^X}, \tag{96}$$

$$w_{i,t+1} = \frac{p_{i,t}^x x_{i,t}}{P_t^X X_t}. \tag{97}$$

Notice that $w_{i,t+1}$ is the nominal cost share of industry i at time t.

For labor productivity it is straightforward to derive that

$$LP_t = \frac{VA_t}{H_t} = \frac{\sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} va_{i,t}}{H_t} \tag{98}$$

$$= \sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{va_{i,t}}{h_{i,t}} \frac{h_{i,t}}{H_t} \tag{99}$$

$$= \sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{h_{i,t}}{H_t} lp_{i,t}. \tag{100}$$

Therefore, I can substitute in equations 93 and 94 with

$$\hat{w}_{i,t} = \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{h_{i,t}}{H_t} \tag{101}$$

$$w_{i,t+1} = \frac{p_{i,t}^{VA} va_{i,t}}{P_t^{VA} VA_t}. \tag{102}$$

For measured TFP, I follow Hulten (1978) and use Domar weights for aggregating gross-output based industry total factor productivity into value-added based aggregate series, which gives me

$$w_{i,t+1} = \frac{p_{i,t} y_{i,t}}{P_t^{VA} VA_t}, \tag{103}$$

where y_i stands for industry gross output and VA stands for aggregate value added.

B.3 Industry-specific weight parameters

The investment good composition weights ξ_i are set to match the cost shares of investment from the 1992 BEA capital-flow table. As the model only features one type of investment, we use the average composition across all industries to calibrate weights ξ_i. BEA capital-flow tables use classification of input commodities that differs from the industry classification in Jorgenson data set, but BEA provides the mapping of commodities into SIC categories. Using this information, the data sets can be almost perfectly mapped into each other. The only exceptions are two BEA commodities *transportation* and *retail trade*, which we can not be match with more detailed categories in the Jorgenson database. We split the goods flow equally between six transportation-related industries (*railroad transportation, local passenger transit, trucking and warehousing, water transport, air transport, transportation services and pipelines*), resp. between two retail industries (*retail trade excluding motor vehicles, retail trade of motor vehicles*). Importantly, the flows of the two problematic commodities into capital formation are small, thus the potential error we create by assuming the equal cost shares is limited.

The consumption composition weights ν_i are set to match the cost shares of consumption from the 1992 BEA input-use table. We include the categories personal consumption expenditures, private residential fixed investment and exports of goods and services. We use six digit level of SIC classification table to map the flows to Jorgenson database industries. Similar problem to capital flow tables emerges for SIC industry *retail trade*, which can not be split into *retail trade excluding motor vehicles* and *retail trade of motor vehicles*. Although the model does not explicitly account for exports and imports, we try to calibrate the industry structure as close to reality as possible. We include exports of goods and services in order to preserve the realistic output shares of the industries. On the other hand, this limits the possibility to interpret ν_i as weights of consumption in the household utility.

B.4 Elasticities σ_y, σ_M

In our model, σ_y is both the firm- and industry-level elasticity of substitution between production factors (k_i, l_i, M_i) in producing output y_i. Optimizing firms choose inputs such that:

$$\frac{k_i}{l_i} = \frac{\mu_{i,K}}{\mu_{i,L}} \left(\frac{w_i}{r^k}\right)^{\sigma_y}, \tag{104}$$

where corresponding FOCs also hold for comparing capital and labor input with intermediate inputs aggregate M_i and its price P_i^M. Constant parameters $\mu_{i,K/L/M}$ are pinned down by the average factor use by industry. Therefore, in the model holds that

$$\ln\left(\frac{k_i}{l_i}\right) = \sigma_y \ln\left(\frac{w_i}{r^k}\right) + \ln\left(\frac{\mu_{i,K}}{\mu_{i,L}}\right), \tag{105}$$

where the last term is constant. Thus, we can obtain σ_y by regressing the simulated data series up to a first order approximation.

Multiplying 104 by prices, we get

$$\begin{aligned} \ln\left(\frac{k_i r^k}{l_i w_i}\right) &= \sigma_y \ln\left(\frac{w_i}{r^k}\right) + \ln\left(\frac{r^k}{w_i}\right) + const. && (106)\\ &= (\sigma_y - 1)\ln\left(\frac{w_i}{r^k}\right) + const. && (107) \end{aligned}$$

where $\sigma_y > 0$, $\eta_y = \sigma_y - 1 > -1$. Taking differences we get

$$d\ln\left(\frac{k_i r^k}{l_i w_i}\right) = \eta_y d\ln\left(\frac{w_i}{r^k}\right) \tag{108}$$

which is the specification we use to compare the model elasticity to the data.

Further, σ_M is the elasticity of substitution between intermediate inputs (m_{ji}) in constructing intermediate input M_i. Optimal behaviour in industry i implies the FOC

$$\frac{m_{j_1,i}}{m_{j_2,i}} = \frac{\alpha_{j_1,i}}{\alpha_{j_2,i}} \left(\frac{p_{j_2}}{p_{j_1}}\right)^{\sigma_M} \tag{109}$$

holds for each j_1, j_2. We can follow the same procedure and obtain the model version of the regression equation for σ_M.

We use equation 108 as identifying assumption and regress the left-hand side on the right-hand side. We compute the regression coefficient as

$$\hat{\eta}_y = corr\left[d\ln\left(\frac{k_i r^k}{l_i w_i}\right), d\ln\left(\frac{w_i}{r^k}\right)\right] \frac{SD\left(d\ln\left(\frac{k_i r^k}{l_i w_i}\right)\right)}{SD\left(d\ln\left(\frac{w_i}{r^k}\right)\right)}. \tag{110}$$

The large number of industry-level series gives 77×3 equations to estimate σ_y and $77 \times \frac{76 \cdot 75}{2}$ equations to estimate σ_M. We use the average across all industry pairs to pin down σ_M. For σ_y we use the average across 77 labor/intermediate inputs coefficients, because the capital accounts are the least reliable of the three production factors. Before computing the simple average elasticity across industries we winsorize all the elasticities smaller than -1.

Using the industry-level information about the labor input and intermediate inputs we obtain $\hat{\sigma}_y = 0.39$. Using other combinations of factors leads to similar estimates, slightly closer to zero. For the estimation of σ_M, using all pairs of industry-to-industry flows, we obtain that $\hat{\sigma}_M = 0.75$. The distribution of the pair-specific $\hat{\sigma}_M$ has a number of strong outliers, therefore winsorizing has a relatively big effect in this case.

B.5 Elasticity σ_U

The combination of σ_e and the elasticity of total labor input σ_U determines the wage elasticity of hours comparable to the standard Frisch elasticity in the aggregate macroeconomic models. The intratemporal FOC 49 implies that

$$-w_{i,t}^h / C_t = U_{h_i}(C_t, N_t) = \kappa N_t^{\frac{1}{\sigma_U} - \frac{1}{\sigma_N}} l_{i,t}^{\frac{1}{\sigma_N}} h_{i,t}^{\frac{\sigma_h}{\sigma_e}}, \tag{111}$$

where w^h is wage per hour, κ is a constant, $\sigma_h = 1$ w.l.o.g., and we can plug in hours and effective labor from equations 40 and 41. It is straightforward to derive the Frisch elasticity as the relationship between a change (simultaneous, in all industries) in hourly wages and hours worked. The Frisch elasticity can be expressed as $\frac{\sigma_U \sigma_e}{\sigma_e + \sigma_U + 1}$. The parameter σ_U is calibrated such that the implied Frisch elasticity is around 0.5, within the range considered in the DSGE literature.

C Additional model results

C.1 Alternative calibration: constant effort

Aggregate variables: second moments									
	Standard dev. relative to output			Correlations with output			Correlations w. measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Constant effort									
Value added	1.00	(0.00)	1.00	1.00	(0.00)	1.00	0.85	(0.06)	0.82
Gross output	1.17	(0.05)	1.03	0.98	(0.00)	0.93	0.80	(0.08)	0.61
Measured TFP	0.62	(0.03)	0.76	0.85	(0.06)	0.82	1.00	(0.00)	1.00
Hours	0.83	(0.07)	0.83	0.86	(0.03)	0.60	0.49	(0.12)	0.07
Intermediate inputs	1.37	(0.09)	1.19	0.95	(0.01)	0.76	0.74	(0.08)	0.35
Inflation	0.93	(0.08)	0.68	0.14	(0.17)	0.52	-0.11	(0.24)	0.05
Labor productivity	0.51	(0.05)	0.82	0.56	(0.13)	0.60	0.89	(0.03)	0.94
Int. inputs per hour	0.77	(0.05)	0.63	0.76	(0.03)	0.65	0.80	(0.03)	0.58
Investment	-	-	2.68	-	-	0.93	-	-	0.68
Consumption	-	-	0.58	-	-	0.81	-	-	0.81
True TFP	-	-	0.63	-	-	0.72	-	-	0.93

Table 9: Comparison of selected second moments in the model and in the data, aggregate variabes. Calibration with constant effort contrasted to the data in the pre-1984 period.

Industry variables: averages across second moments									
	Standard dev. relative to output			Correlations with output			Correlations w measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Constant effort									
Value added	1.00	(0.06)	1.00	1.00	(0.00)	1.00	0.78	(0.01)	0.69
Gross output	0.71	(0.00)	0.79	0.84	(0.01)	0.88	0.57	(0.01)	0.39
Measured TFP	0.36	(0.01)	0.35	0.78	(0.01)	0.69	1.00	(0.00)	1.00
Hours	0.56	(0.02)	0.77	0.38	(0.02)	0.45	-0.02	(0.03)	-0.23
Intermediate inputs	0.83	(0.01)	0.81	0.35	(0.04)	0.56	0.14	(0.02)	-0.04
Prices	0.66	(0.03)	0.21	-0.33	(0.01)	-0.32	-0.43	(0.02)	-0.54
Input prices	0.33	(0.04)	0.10	-0.13	(0.02)	-0.15	-0.16	(0.02)	-0.23
Labor productivity	0.95	(0.04)	0.82	0.72	(0.01)	0.61	0.84	(0.01)	0.96
Int. inputs per hour	0.73	(0.02)	0.30	0.17	(0.04)	0.29	0.22	(0.04)	0.41
True TFP	-	-	0.32	-	-	0.55	-	-	0.91

Table 10: Comparison of selected second moments in the model and in the data, industry variables. Calibration with constant effort contrasted to the data in the pre-1984 period. Reported numbers are weighted (by industry output) averages across industry moments.

Cross-Industry Correlations			
Constant effort	Data	(SE)	Model
Value added	0.14	(0.009)	0.15
Gross output	0.22	(0.015)	0.24
Measured TFP	0.05	(0.008)	0.13
Hours	0.20	(0.011)	0.15
Intermediate inputs	0.19	(0.035)	0.25
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.21
Labor productivity	0.02	(0.006)	0.13
True TFP	-	-	0.12

Table 11: Average cross-industry pairwise correlations. Calibration with constant effort contrasted to the data in the pre-1984 period.

Variance Decomposition: constant effort					
Shocks	Aggregate		Industry		Measurement
	technology	demand	technology	demand	error
Industry variables					
Value added	0.09	0.07	0.22	0.61	0.00
Gross output	0.06	0.16	0.04	0.73	0.00
Measured TFP	0.11	0.01	0.78	0.03	0.07
Hours	0.02	0.13	0.12	0.60	0.12
Intermediate inputs	0.03	0.22	0.12	0.61	0.00
Output price	0.02	0.03	0.94	0.01	0.00
Labor productivity	0.12	0.01	0.70	0.06	0.10
Investment good production	0.31	0.61	0.10	0.00	0.00
Consumption	0.00	0.00	0.00	0.99	0.00
True TFP	0.10	0.00	0.90	0.00	0.00
Aggregate variables					
Value added	0.52	0.39	0.10	0.00	0.00
Gross output	0.24	0.69	0.06	0.02	0.00
Measured TFP	0.75	0.03	0.13	0.00	0.08
Hours	0.02	0.78	0.02	0.00	0.16
Intermediate inputs	0.07	0.84	0.03	0.06	0.00
Inflation	0.02	0.96	0.01	0.01	0.00
Labor productivity	0.68	0.02	0.12	0.00	0.16
Investment	0.30	0.61	0.09	0.00	0.00
Consumption	0.76	0.08	0.13	0.02	0.00
True TFP	0.84	0.00	0.14	0.00	0.00

Table 12: Variance decomposition of selected model variables. Calibration with constant effort.

C.2 Alternative calibration: Flexible RBC model

Aggregate variables: second moments									
	Standard dev. relative to output			Correlations with output			Correlations w. measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Flexible prices									
Value added	1.00	(0.00)	1.00	1.00	(0.00)	1.00	0.85	(0.06)	0.96
Gross output	1.17	(0.05)	0.80	0.98	(0.00)	0.99	0.80	(0.08)	0.96
Measured TFP	0.62	(0.03)	0.69	0.85	(0.06)	0.96	1.00	(0.00)	1.00
Hours	0.83	(0.07)	0.51	0.86	(0.03)	0.81	0.49	(0.12)	0.65
Intermediate inputs	1.37	(0.09)	0.60	0.95	(0.01)	0.95	0.74	(0.08)	0.92
Inflation	0.93	(0.08)	1571.35	0.14	(0.17)	-0.01	-0.11	(0.24)	-0.01
Labor productivity	0.51	(0.05)	0.66	0.56	(0.13)	0.89	0.89	(0.03)	0.96
Int. inputs per hour	0.77	(0.05)	0.38	0.76	(0.03)	0.42	0.80	(0.03)	0.58
Investment	-	-	3.09	-	-	0.91	-	-	0.86
Consumption	-	-	0.57	-	-	0.63	-	-	0.65
True TFP	-	-	0.53	-	-	0.98	-	-	0.97

Table 13: Comparison of selected second moments in the model and in the data, aggregate variabes. Calibration with flexible prices contrasted to the data in the pre-1984 period.

Industry variables: averages across second moments									
	Standard dev. relative to output			Correlations with output			Correlations w measured TFP		
	Data	(SE)	Model	Data	(SE)	Model	Data	(SE)	Model
Flexible prices									
Value added	1.00	(0.06)	1.00	1.00	(0.00)	1.00	0.78	(0.01)	0.78
Gross output	0.71	(0.00)	0.67	0.84	(0.01)	0.95	0.57	(0.01)	0.62
Measured TFP	0.36	(0.01)	0.34	0.78	(0.01)	0.78	1.00	(0.00)	1.00
Hours	0.56	(0.02)	0.57	0.38	(0.02)	0.46	-0.02	(0.03)	-0.07
Intermediate inputs	0.83	(0.01)	0.56	0.35	(0.04)	0.63	0.14	(0.02)	0.18
Prices	0.66	(0.03)	0.34	-0.33	(0.01)	-0.45	-0.43	(0.02)	-0.65
Input prices	0.33	(0.04)	0.16	-0.13	(0.02)	-0.21	-0.16	(0.02)	-0.29
Labor productivity	0.95	(0.04)	0.84	0.72	(0.01)	0.76	0.84	(0.01)	0.97
Int. inputs per hour	0.73	(0.02)	0.25	0.17	(0.04)	0.25	0.22	(0.04)	0.45
True TFP	-	-	0.30	-	-	0.69	-	-	0.93

Table 14: Comparison of selected second moments in the model and in the data, industry variables. Calibration with flexible prices contrasted to the data in the pre-1984 period. Reported numbers are weighted (by industry output) averages across industry moments.

Cross-Industry Correlations			
Flexible prices	Data	(SE)	Model
Value added	0.14	(0.009)	0.19
Gross output	0.22	(0.015)	0.20
Measured TFP	0.05	(0.008)	0.18
Hours	0.20	(0.011)	0.09
Intermediate inputs	0.19	(0.035)	0.13
Output price	0.07	(0.015)	0.01
Input price	0.15	(0.017)	0.20
Labor productivity	0.02	(0.006)	0.16
True TFP	-	-	0.17

Table 15: Average cross-industry pairwise correlations. Calibration with flexible prices (RBC benchmark) contrasted to the data in the pre-1984 period.

Variance Decomposition: flexible prices					
Shocks	Aggregate		Industry		Measurement
	technology	demand	technology	demand	error
Industry variables					
Value added	0.17	0.00	0.50	0.33	0.00
Gross output	0.19	0.00	0.23	0.57	0.00
Measured TFP	0.13	0.00	0.80	0.02	0.05
Hours	0.08	0.00	0.15	0.61	0.15
Intermediate inputs	0.15	0.00	0.15	0.69	0.00
Output price	0.03	0.00	0.96	0.01	0.00
Input price	0.03	0.00	0.96	0.01	0.00
Labor productivity	0.12	0.00	0.78	0.03	0.07
Investment good production	0.46	0.00	0.53	0.00	0.00
Consumption	0.00	0.00	0.00	1.00	0.00
True TFP	0.10	0.00	0.89	0.00	0.00
Aggregate variables					
Value added	0.66	0.00	0.34	0.00	0.00
Gross output	0.64	0.00	0.34	0.01	0.00
Measured TFP	0.72	0.00	0.22	0.00	0.05
Hours	0.33	0.00	0.46	0.00	0.22
Intermediate inputs	0.57	0.00	0.33	0.08	0.00
Inflation	0.00	1.00	0.00	0.00	0.00
Labor productivity	0.66	0.00	0.19	0.00	0.13
Int. inputs per hour	0.25	0.00	0.12	0.22	0.40
Investment	0.44	0.00	0.56	0.00	0.00
Consumption	0.66	0.00	0.30	0.02	0.00
True TFP	0.79	0.00	0.21	0.00	0.00

Table 16: Variance decomposition of selected model variables. Calibration with flexible prices contrasted to the data in the pre-1984 period.

C.3 Additional robustness checks

In all robustness exercises, the variance of aggregate technology shock is zero. All alternative model calibrations deliver qualitatively similar results, with the exception of the version with zero measurement errors, see tables 18 and 17. Omitting the measurement errors increases the aggregate correlations between aggregate variables, but does not change the main results.

Robustness checks: industry variables								
	baseline	heter. θ_i	$\kappa = 10$	$\sigma_U = 3$	$\sigma_e = 3$	$\sigma_N = 2$	$\sigma_M = 0.3$	measure. error $= 0$
St. dev. relatiove to value added								
Value added	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gross output	0.84	0.76	0.84	0.83	0.83	0.85	0.85	0.85
Measured TFP	0.38	0.35	0.40	0.36	0.37	0.39	0.39	0.39
Hours	0.60	0.51	0.61	0.59	0.65	0.58	0.62	0.52
Intermediate inputs	0.92	0.77	0.94	0.87	0.89	0.96	0.96	0.95
Prices	0.25	0.46	0.27	0.24	0.24	0.28	0.27	0.27
Input prices	0.11	0.21	0.12	0.10	0.11	0.12	0.12	0.12
Labor productivity	0.86	0.89	0.89	0.83	0.84	0.89	0.88	0.84
Int. inputs/hour	0.52	0.43	0.54	0.46	0.43	0.57	0.53	0.44
True TFP	0.36	0.32	0.38	0.34	0.35	0.37	0.38	0.38
Correlation with measured TFP								
Value added	0.81	0.82	0.81	0.81	0.77	0.81	0.80	0.86
Gross output	0.55	0.58	0.54	0.57	0.49	0.55	0.51	0.57
Measured TFP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hours	-0.06	-0.06	-0.09	-0.03	-0.11	-0.07	-0.10	0.11
Intermediate inputs	0.18	0.14	0.16	0.18	0.10	0.17	0.15	0.17
Prices	-0.54	-0.60	-0.54	-0.52	-0.56	-0.50	-0.53	-0.60
Input prices	-0.21	-0.27	-0.21	-0.20	-0.20	-0.19	-0.20	-0.24
Labor productivity	0.94	0.97	0.93	0.94	0.94	0.94	0.93	0.94
Int. inputs/hour	0.38	0.36	0.36	0.38	0.35	0.35	0.36	0.25
True TFP	0.73	0.76	0.75	0.73	0.82	0.74	0.73	0.79
Cross-industry correlations								
Value added	0.13	0.08	0.14	0.13	0.12	0.13	0.14	0.14
Gross output	0.30	0.16	0.33	0.27	0.28	0.30	0.30	0.33
Measured TFP	0.07	0.04	0.07	0.07	0.06	0.07	0.07	0.07
Hours	0.20	0.13	0.20	0.20	0.18	0.21	0.18	0.24
Intermediate inputs	0.36	0.21	0.39	0.31	0.33	0.35	0.34	0.39
Prices	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Input prices	0.21	0.13	0.22	0.22	0.23	0.22	0.21	0.21
Labor productivity	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.03
Int. inputs/hour	0.40	0.28	0.44	0.30	0.39	0.35	0.40	0.58
True TFP	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00

Table 17: Robustness checks: comparison of moments across various model calibrations. Industry variables (weighted average across industries).Heter. θ_i: heterogeneous price rigidity parameters across industries as estimated in Bouakez et al. (2014). Measure. error = 0: model version without measurement error shock.

Robustness checks: aggregate variables								
	baseline	heter. θ_i	$\kappa = 10$	$\sigma_U = 3$	$\sigma_e = 3$	$\sigma_N = 2$	$\sigma_M = 0.3$	measure. error = 0
St. dev. relatiove to value added								
Value added	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gross output	1.32	1.24	1.34	1.21	1.27	1.31	1.31	1.31
Measured TFP	0.59	0.60	0.61	0.58	0.59	0.60	0.60	0.54
Hours	0.81	0.76	0.80	0.81	0.87	0.80	0.80	0.72
Intermediate inputs	1.68	1.53	1.72	1.46	1.60	1.67	1.66	1.67
Inflation	1.01	2.85	1.35	0.81	0.96	1.01	1.01	1.01
Labor productivity	0.54	0.60	0.56	0.53	0.58	0.55	0.55	0.39
Int. inputs/hour	1.04	0.96	1.09	0.84	0.93	1.04	1.03	0.95
Investment	3.29	4.07	2.88	3.24	3.20	3.25	3.27	3.28
Consumption	0.35	0.52	0.44	0.36	0.40	0.36	0.35	0.34
True TFP	0.27	0.31	0.29	0.26	0.35	0.27	0.28	0.26
Correlation with measured TFP								
Value added	0.87	0.85	0.87	0.88	0.83	0.88	0.88	0.96
Gross output	0.82	0.79	0.81	0.83	0.73	0.82	0.82	0.90
Measured TFP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hours	0.49	0.41	0.47	0.51	0.37	0.48	0.48	0.83
Intermediate inputs	0.77	0.72	0.76	0.78	0.65	0.77	0.77	0.85
Inflation	0.72	0.45	0.72	0.72	0.56	0.72	0.71	0.80
Labor productivity	0.88	0.89	0.89	0.88	0.87	0.89	0.89	0.91
Int. inputs/hour	0.87	0.82	0.86	0.86	0.77	0.87	0.86	0.86
Investment	0.83	0.78	0.83	0.84	0.76	0.83	0.83	0.92
Consumption	0.64	0.07	0.78	0.65	0.68	0.65	0.64	0.71
True TFP	0.40	0.51	0.44	0.43	0.61	0.42	0.43	0.45

Table 18: Robustness checks: comparison of moments across various model calibrations. Aggregate variables. Heter. θ_i: heterogeneous price rigidity parameters across industries as estimated in Bouakez et al. (2014). Measure. error = 0: model version without measurement error shock.

D Gross output versus value added fluctuations

Technology and demand shocks have different effects on the ratio of gross output versus net output fluctuations. This can be illustrated most easily in the case of a Leontieff technology. Assume the aggregate production function

$$Y = A \min\{L, M\}, \qquad A > 1 \tag{112}$$

for gross output Y with the factors labor L and intermediate inputs M. Value added is then given by $VA = Y - M$. Cost minimization implies $L = M$ and therefore

$$VA = (A-1)L. \tag{113}$$

Variations in A (technology shocks), keeping labor input L constant, then imply

$$\frac{dY/dA}{Y} \Big/ \frac{dVA/dA}{VA} = \frac{L}{L}\frac{(A-1)L}{AL} = \frac{A-1}{A} < 1, \tag{114}$$

which means that gross output fluctuates proportionally less than value added. In contrast, variations in L for constant A, as they arise from demand shocks, lead to

$$\frac{dY/dA}{Y} \Big/ \frac{dVA/dA}{VA} = \frac{A}{A-1}\frac{(A-1)L}{AL} = 1, \tag{115}$$

so that gross and net output fluctuate equally strongly. This toy model does not make gross output fluctuate more than value added, but it shows that demand fluctuations generate fluctuations in gross output which are bigger than technology shocks.